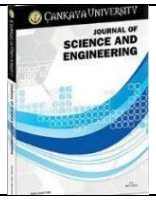
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Integrated Production and Distribution Scheduling: A Systematic Review of Problem Characteristics and Solution Methods

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Keywords

Integrated Production and Distribution Scheduling, Systematic Review, Scheduling, Supply Chain Optimization.

Abstract

The integrated approach to scheduling production and distribution activities, along with the development of solution methods, has been extensively studied due to industrial demand. This paper presents a systematic review of the classification characteristics of integrated production and distribution scheduling (IPDS). The granular decomposition method is utilized as the systematic review methodology. We provide a classification of problem characteristics and solution methods to identify research trends and gaps. The research was conducted using two primary search databases: Scopus and Web of Science (WoS). In total, we identify relevant articles published between 2010 and 2025. We highlight the current state of the art and future directions of the IPDS problem.

1. Introduction

The Integrated Production and Distribution Scheduling (IPDS) problem has gained popularity, particularly since 2010. The traditional method treats production and distribution scheduling as separate activities. This approach creates local efficiencies but leads to global sub-optimization, potentially decreasing the supply chain's competitiveness or sustainability. In contrast, the IPDS approach is valued for its advantages, as it delivers optimal results throughout the process and provides a cost-effective solution for businesses.

Recent market trends, including the rise of e-commerce and omnichannel retailing, have established IPDS as a vital strategic necessity rather than just a standard operational improvement [1], [2]. The growing demand for highly customized products [3], means that customers now expect flexible, low-cost, and rapid deliveries, rather than traditional batch transportation. To achieve this, optimizing delivery routes to minimize carbon emissions involves striking a complex balance between customer-focused agility and environmentally friendly logistics [4], [5]. This process increasingly relies on digitization and real-time data analytics, enabling transformational agility and collaborative decision-making that modern supply chains need [6], [7].

The revolution in manufacturing and delivery industries, fueled by the Internet of Things (IoT) and cyber-physical systems (CPS) that leverage this data, allows for intelligent manufacturing and delivery systems to incorporate IPDS as a key component. Automated guided vehicles (AGVs) are commonly used for internal material transportation in intelligent systems. The growing controllability of these smart logistics devices provides a dependable basis for creating lean schedules, ultimately increasing productivity and reducing overall operation

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costs [8]. IoT-connected, responsive, and autonomous delivery systems can improve just-in-time delivery performance [9].

IPDS supports the primary goals of both lean and agile manufacturing: it demonstrates leanness by reducing waste and inventory costs and fosters agility by enabling prompt responses to customer demand. Traditionally referred to as "leagility," faster responses by businesses to market demand with fewer workers, materials, and machines are explored [10]. To meet the needs of leagile manufacturing, developing an IPDS system becomes essential [11]. For a company to implement a truly successful just-in-time (JIT) strategy, scheduling activities outside the factory in coordination with production activities is crucial [12].

Despite advances in computational technology, the NP-hardness of IPDS problems remains a major challenge in finding exact solutions for medium- to large-sized instances. Comprising already NP-hard problems like vehicle route planning (VRP), the traditional traveling salesman problem (TSP), and static or dynamic lot-sizing problems (LSP), IPDS naturally becomes a computationally intensive NP-hard issue [13], [14]. Because of this, the approach to solving these problems often relies on approximate algorithms, such as heuristics and metaheuristics, rather than exact methods. Current market trends are creating an urgent need for faster, more adaptive scheduling algorithms to manage the growing volume of customer orders. E-commerce retailers, for example, must assemble large numbers of small orders within tight time frames, such as for next-day or same-day delivery [15].

A systematic review of IPDS is essential given the topic's inherent complexity and the rapidly growing body of research across multiple fields relevant to this context. Besides the diverse research subtopics within IPDS, many studies focus on addressing problems with large optimality gaps using heuristic and metaheuristic approaches. The primary objective of this work is to categorize problem settings and solution methods, and to conduct both qualitative and quantitative analyses of the current state of the field. Articles selected from the literature were systematically evaluated to identify established research trends and highlight critical gaps.

2. Previous Review and Systematic Review Studies

The Review study by [16] is a key work that defines and categorizes the problem structure of the emerging field of IPDS. This study employs a mathematical five-field notation to classify and analyze a diverse range of models, encompassing machine configuration, order constraints, delivery characteristics, number of customers, and objective functions. At the time of the study, fixed delivery departures, heterogeneous vehicles, and multi-plant environments were identified as underexplored areas in IPDS research.

The systematic literature review by [17] offers a comprehensive analysis of quantitative methods for integrating production and distribution planning (IPDP) within supply chains. It proposes a detailed classification framework based on eight dimensions, including decision level, problem structure, and solution approaches such as optimization software, metaheuristics, and emerging machine learning techniques. An in-depth analysis of data collected through systematic research reveals a dominance of mixed-integer linear programming models and tactical-level decision-making, with limited adoption of stochastic and multi-objective approaches, despite the prevalence of real-world uncertainties.

Another systematic review [18] focuses on further research regarding production planning and scheduling in multi-factory network articles. Genetic algorithms and iterated greedy algorithms are among the most common metaheuristic methods, primarily because these problems are NP-hard and require managing computational complexity. The authors highlight a strong research focus on makespan minimization in flow shop and job shop setups, while noting less-explored areas such as due date-related objectives, stochastic parameters, and transportation issues.

Green supply chain management (GSCM) research was reviewed by [19], covering articles from 2006 to 2016. The study found that the primary focus of GSCM work is on highlighting financial impacts and operational benefits within the supply chain, rather than environmental factors. This research, primarily driven by empirical data and focused on manufacturing sectors such as automotive and electronics, is notable for its use of surveys and fuzzy multi-criteria decision-making models to address challenges, including supplier selection. By summarizing these key points, the review consolidates existing knowledge and clearly identifies important research gaps, particularly in less-studied sectors such as pharmaceuticals and public administration.

[20] offers a comprehensive, well-organized review of research on Aggregate Production Planning (APP), which involves determining medium-term production, inventory, and workforce levels. The authors systematically analyze over 200 research papers published in the past 50 years. They categorize these studies based on features such as the types of models used, solution methods applied, and how they handle uncertainty. The primary objective of this review is to understand the current state of research and explore how APP can be integrated with the principles of Sustainable Development and Circular Economy through modern digital technologies. The study also highlights limitations in existing research and suggests future directions, emphasizing the need for more sustainable and socially responsible production planning in today's industrial landscape.

There are highlighted critical reviews and systematic reviews of research on production, scheduling, and supply chain. IPDS problem research typically focuses on synchronizing manufacturing and logistics activities to minimize total cost or lead time, often emphasizing deterministic or stochastic optimization models, heuristic solutions, and coordination mechanisms between production and distribution stages. A systematic, in-depth analysis of the IPDS study, identifying trends in problem categorization and solution methods — specifically, exact and heuristic methods — is lacking in the literature. This paper effectively analyzes and categorizes the current state of the art and the characteristics of the IPDS study.

3. Review Methodology

The design of this systematic review is similar to the [17] systematic review article, which follows the methodology outlined in [21] to establish a systematic structure. For the analysis, a three-step approach: (a) planning, (b) conducting, and (c) reporting and dissemination [22] was used as the main progression. Planning is described in the introduction section, conduct is detailed in the review methodology section, and reporting and dissemination are covered in the problem structure and solution methodology sections. A systematic, reproducible, and transparent methodological approach is used for the study. Our results are precise and repeatable, enabling any researcher to build upon our work now or in the future.

The first step in conducting a systematic review research is constructing the article list. The last additions to the list were completed in October 2025. Web of Science (WoS) and Scopus were preferred for the research. These databases collectively provide extensive coverage of the world's leading peer-reviewed journals in engineering, computer science, and operations research, which are the core disciplines required for an IPDS systematic review. Additionally, the functional filtering tools in these databases facilitate researchers in efficiently including and excluding studies to narrow down to a focused, relevant collection of IPDS articles.

IPDS is a well-defined topic in the literature that can be distinguished from other operations research topics by the title of the article. [23] reported a double screening method aimed at avoiding the non-detection of relevant evidence and ensuring the validity of conclusions drawn from the available evidence. According to this method, titles or abstracts are used for the initial screening to exclude irrelevant articles. Full texts are then obtained and reviewed in the second screening step. This approach essentially reduces the workload to complete the work within a specified time frame. The initial search strategy was designed to capture literature on the integrated production, distribution, and scheduling (IPDS) domain. Core conceptual groups were defined as "integration," "production," and "distribution." However, a preliminary search revealed that this combination mainly yielded

articles on Integrated Production and Distribution Planning (IPDP), a broader field that often excludes detailed scheduling considerations. To refine the results and improve their relevance to scheduling, the keyword "scheduling" was incorporated into the search string.

The search was conducted within article titles to enhance accuracy. The words "production" and "scheduling" had to be in the title, as they lack common synonyms and are crucial to the research focus. The term "distribution," along with its alternatives "outbound" and "vehicle routing," is used collectively to encompass a broad range of articles, as various studies employ different terminology. Additionally, to exclude unrelated topics such as preventive maintenance, the term "maintenance" was added with the "NOT" operator. This effectively filtered out a few irrelevant publications. The full search logic applied to article titles is detailed in Table 2.

Table 1. Search logic applied to WoS and Scopus databases to form a list of IPDS publications.

Concept	**Purpose / Rationale**	**Keywords & Operators**	**Field Applied**
Core Concept 1	To capture the integrative aspect of the problem. Synonyms are used to broaden the capture.	integrated OR joint	Title
Logical Operator	To mandate Core Concept 2 is present in the title.	AND	Title
Core Concept 2	To mandate the presence of the core term "production"	production	Title
Logical Operator	To mandate Core Concept 3 is present in the title.	AND	-
Core Concept 3	To capture the distribution component, using key terms synonymous with logistics and delivery.	distribution OR outbound OR vehicle routing	Title
Logical Operator	To mandate Core Concept 4 is present in the title.	AND	-
Core Concept 4	To mandate the presence of the central, unambiguous term "scheduling". This refines the broader IPDP field to focus on scheduling.	scheduling	Title
Logical Operator	To explicitly exclude articles containing the exclusion term.	NOT	-
Exclusion Concept 1	To filter out unrelated literature in the domain of preventive maintenance, which also uses "scheduling".	maintenance	Title

The initial screening identified 98 articles from Scopus and 82 from WoS. Applying exclusion criteria refined these datasets. According to the WoS results, two articles were removed because they focused on maintenance, four were review articles, four were published before 2010, and four were inaccessible. Additionally, articles not published in academic journals or in languages other than English were excluded. This process resulted in 64 articles from WoS and 63 from Scopus for further analysis.

Subsequently, the articles from both databases were combined. A second screening phase identified 59 overlapping articles present in both lists. The final consolidated list included 68 unique articles, of which five were exclusive to WoS and four to Scopus. Figure 1 presents a schematic of the identification and screening process, while Table 2 shows the article counts by source and their intersection.

The distribution of the 68 selected articles by source journal was analyzed to identify the main publication venues in this field. The results are summarized in Table 3. According to the table, China is the leading contributor, with 26 articles (38.2%). This is followed by Iran, known for its strong mathematical traditions and emphasis on

operational optimization, with 13 articles (19.1%), and Turkey, an important logistics and manufacturing hub between Europe and Asia, with 6 articles (8.8%). The remaining 23 articles (33.8%) originate from 16 other countries. Except for the USA, each of these countries contributes less than 5%. These findings are likely influenced by global economic factors and academic traditions.

Table 2. Consolidated list counts from Scopus and WoS databases.

Category	Count
Total in Scopus	63
Total in WoS	64
Articles in Both Databases	59
Articles Only in Scopus	4
Articles Only in WoS	5
Total Number of Articles	68

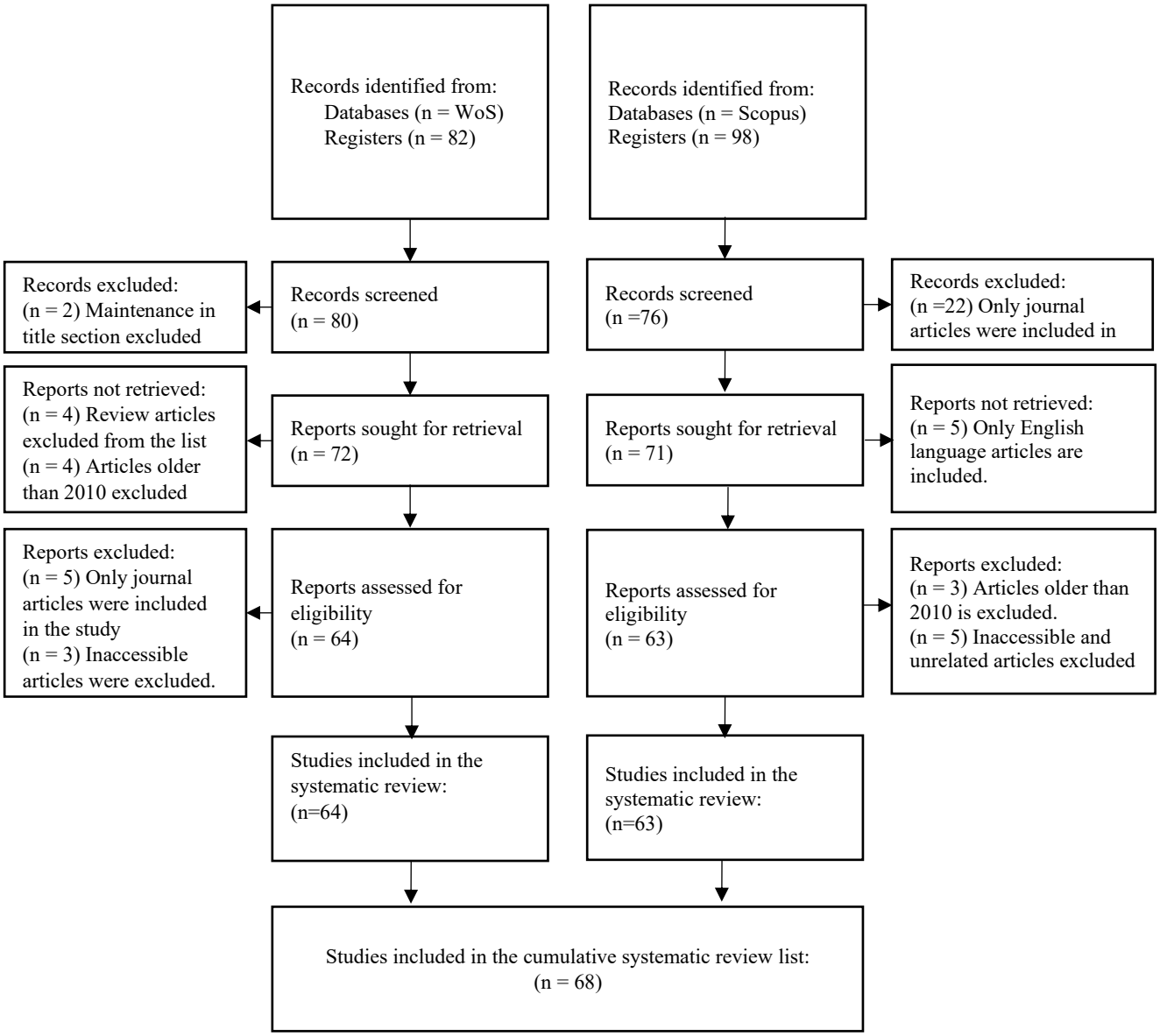


Figure 1. Schematic representation of the identification and screening process from WoS and Scopus databases, containing exclusion and inclusion processes and the final count from each database.

Table 3. Number of articles from each country in the final list after the double screening process.

Country	Count of Country	Percent
China	26	38.2
Iran	13	19.1
Turkey	6	8.8
USA	4	5.9
Canada	2	2.9
Germany	2	2.9
Hong Kong	2	2.9
Poland	2	2.9
Bangladesh	1	1.5
Belgium	1	1.5
Brazil	1	1.5
China	1	1.5
France	1	1.5
Hungary	1	1.5
India	1	1.5
Indonesia	1	1.5
Iran	1	1.5
Morocco	1	1.5
Serbia	1	1.5
Grand Total	**68**	**100.00**

The distribution of selected articles, sorted by frequency of counts in the source journals, is shown in Figure 2. The analysis of publication venues for the 68 articles included in this systematic review reveals a distinctly interdisciplinary yet centralized intellectual landscape for research in IPDS. A wide range of articles is published across various journals. The most frequently appearing journals, in descending order, are the International Journal of Production Research, Computers & Industrial Engineering, and Computers & Operations Research, together accounting for 22% of the total. This core is complemented by a significant cluster of journals specializing in applied computational intelligence, such as Expert Systems with Applications and Engineering Applications of Artificial Intelligence, highlighting the field's reliance on heuristics and metaheuristics to address problem complexity. At the same time, the presence of mathematically oriented outlets like Applied Mathematical Modelling and Omega underscores the importance of model formulation and exact solutions. Overall, the journal ecosystem is characterized by a collaborative interplay between integrated production research, supply chain optimization, mathematical optimization, and advanced heuristic methods, reflecting the complex and multifaceted nature of the IPDS problem.

The IPDS problem has attracted sustained and increasing interest among operations researchers from 2010 to 2025. The publication frequency, as shown in Figure 3, demonstrates an upward trend, highlighting IPDS as an actively evolving research area. After a slow start with only a few cumulative annual publications until 2015, the number of publications grew afterward. The years 2024, 2015, and 2018 show peaks, indicating temporary increases in the topic's popularity. Between 2010 and 2015, 14 publications were produced. From that point on, the number of publications increased every five years, with 25 publications from 2015 to 2020 and 29 from 2020 to 2025. This steady growth establishes IPDS as a maturing and active field within operations research.

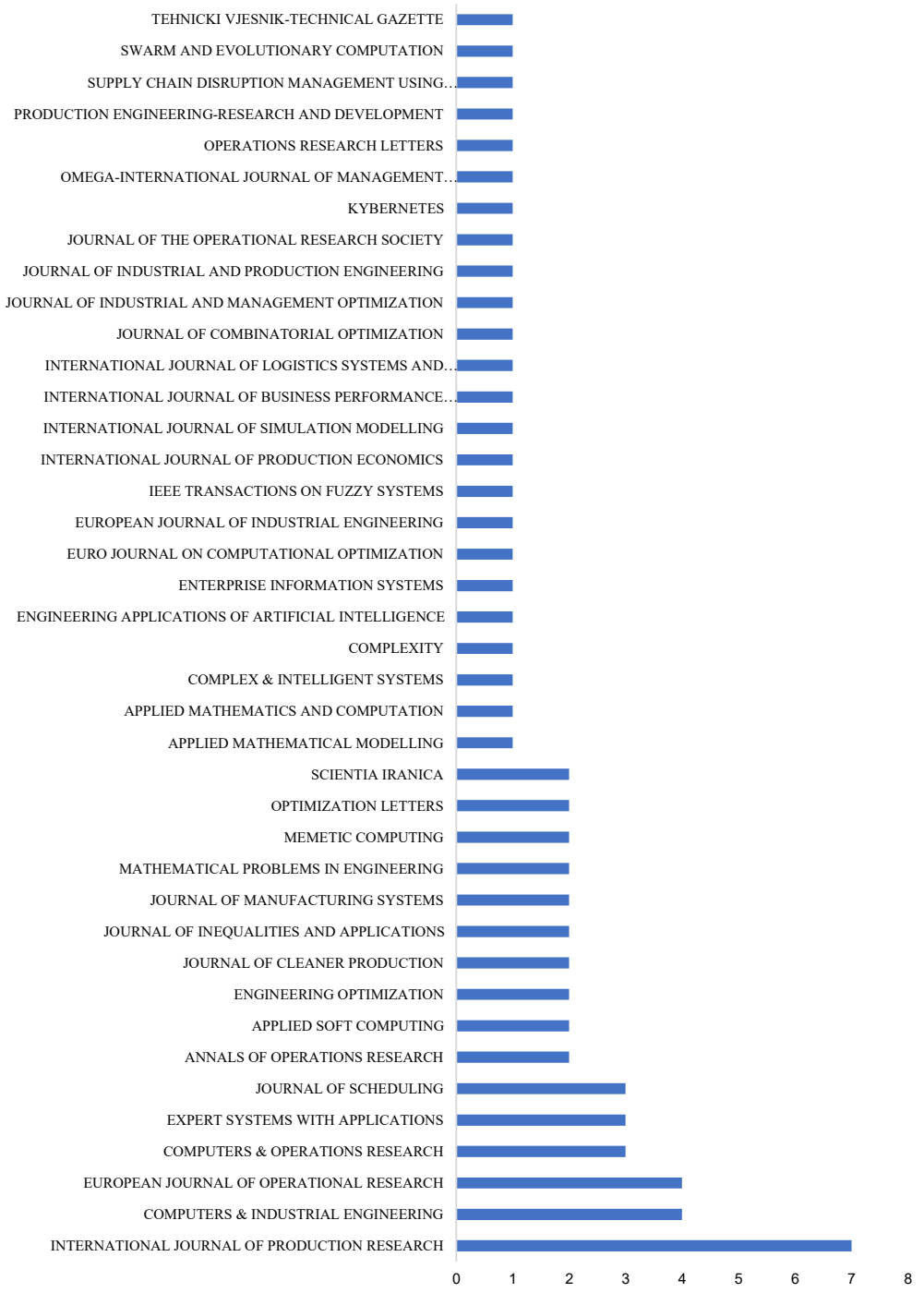


Figure 2. Distribution of the selected articles by source journal and frequency of each journal by count of articles.

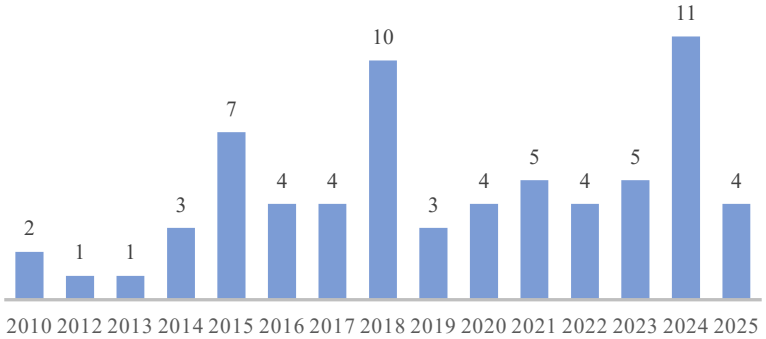


Figure 3. Frequency of publications of IPDS articles between the years 2010-2025.

4. Mathematical Description of the Problem

The IPDS problem essentially involves scheduling production across a multi-factory supply chain and planning vehicle routing problems (VRPs) to deliver products or services. The system consists of multiple factories, $f = 1,2,\dots,F$ and a set of customer orders $k,i,j = ,2,\dots,K$. Each factory is equipped with several machines $m_1, m_2, \dots, m_M$, where machine configurations may be single-machine, parallel-machine, or shops with multiple operations, such as flow shops, hybrid flow shops, job shops, etc. Customer orders consist of demands for one or more of these products $n_1, n_2, \dots, , n_N$. The machines, with custom configurations tailored to each scenario, process each customer's orders. Orders may include the following parameters, depending on the problem elements:

- A release date $r_{k,n}$ is when the order is ready for processing,
- Processing positions $p = 1,2 , \dots, P$ and production completion times at each factory and machine C_p^f,
- Direct shipment or single or multiple warehouses that collect products before the shipment, with an inventory of I_m^f,
- A homogeneous or heterogeneous capacity of vehicles c_v,
- A fixed delivery time fd_k or delivery time window $[A_i, B_j]$ where the order must be delivered unless a penalty cost occurs,
- $T_{i,j}$ time or distance between customers i and j.
- Revenue of the order R_k.

In static models, vehicles are available at the plant at the start and deliver the products to the customers at various locations. In dynamic models, multiple vehicle tours are involved in some works, whereas others assume each vehicle makes only one tour. Vehicles utilized for delivery may be homogeneous, where c_k is the capacity of each vehicle k of the set K. The vehicle's capacity may be limited or infinite. Vehicles may deliver a set of orders n to several customers, making a round trip or a sequence, or each vehicle may carry only orders for a specific customer. Number of vehicles V may be infinite, one $V \geq 1, V \epsilon Z$. Transportation times and costs are generally included in the objective functions.

Solving the IPDS problem yields the optimal production schedule, which determines when, where, and how much to produce goods, as well as a distribution schedule that specifies the number of transportation resources utilized, vehicle routes, characteristics, and work sequences. Completion C_p^f, departure S_k^f and delivery time D_k^f of order k are the definitions used to calculate the makespan to satisfy customer orders:

- $min \sum D_k^f$ or
- $\min(max\, D_k^f)$

Delivery lateness, tardiness, and earliness of an order can be described as follows:

- $L_k = D_k^f - S_k^f$, the delivery lateness of the order k.
- $T_k = max(0, D_k^f - S_k^f)$, the delivery tardiness of the order k.
- $E_k = max(0, D_k^f - C_p^f)$, the completion earliness of the order k.

The objective function of IPDS problems is configured in terms of cost-based, revenue-based, time-based, and green-based elements. Cost-based elements include the sum of one or more of the transportation costs. These costs include tour-based expenses generated by all individual delivery trips, which may depend on the distance travelled by the vehicle and the number of vehicles. Transportation costs may also be fixed. The production step includes costs that stem from the time and type of production resources used. Setup times, process time, and machine operation costs are some sources of production costs. In revenue-based objectives, the total revenue of orders delivered to customers is maximized. Green considerations in the objective function involve studies that

incorporate limited-life products, environmental impact calculations, or vehicle greenhouse gas emissions into the problem.

5. Problem Characteristics of the IPDS Problem

The production organization of IPDS problems involves various customization elements that describe the characteristics of the production facility. The scheduling of the production area depends on the machine configuration within the production facilities. Customer demands are composed of a single product or multiple products. The products are either stored in the production facility's stock area or in a depot before shipment. Products are distributed to customers using homogeneous or heterogeneous vehicles, or a single vehicle. Distribution scheduling on planned routes is defined by single or multiple tours from the production facility or depot to customers. Soft or hard time windows may be present as distribution constraints, and the earliness and tardiness decision variables depend on them. Some problems may contain a single period of scheduling, while others involve multi-period problems. These characteristics are explored in the following sections.

5.1. Machine Configuration

5.1.1. Single Machine

A single-machine environment in a production line or facility represents the scheduling of all jobs or products sequentially on a single shared manufacturing resource. This environment abstracts a production facility with a specialized piece of equipment, or a simplified production cell. In an IPDS setting, the single-machine assumption of the production environment significantly reduces the complexity of the production scheduling sub-problem by eliminating challenges related to parallel or sequential processing routes and machine assignments between workstations.

Traditional scheduling rules for a single-machine environment are often applied to IPDS problems in early models. Earliest Due Date (EDD) and Shortest Processing Time (SPT) are used to form optimal schedules and heuristic models in [24], [25]. Scheduling of production in a single machine environment evolved from simple sequencing of jobs to optimal schedules to minimizing costs and service levels of competing customers. Non-delay schedules in a single-machine environment are widely used in traditional problems. Processing of each product type continues after the prior one ends, and the departure time of vehicles is the exact time of production finish [26]. In contrast, highly integrated problems, including complex vehicle routing scenarios and inventory holding costs, may require “unforced idleness” to achieve a Pareto-optimal solution [27].

5.1.2. Parallel Machines

A parallel machine environment is a production configuration in which a set of m machines operate concurrently, each capable of processing any job from a given set of k orders. Each order is assigned to a machine and sequenced, resulting in two independent decisions that arise from the problem solution. Parallel machines are identical machines that can process the same products at the same rate. As opposed, non-identical parallel machines are the opposite. Non-identical parallel machines can also be characterized as dedicated parallel machines; each machine is dedicated to a single product. This environment model is common in industrial settings, such as multiple identical CNC machines in a manufacturing line, packaging lines, or assembly workshops, where machines work in parallel.

The chemotherapy production and delivery process is addressed as an IPDS problem in [28]. Each order must be produced by technicians working at benches arranged in parallel machine configurations. This corresponds to a heterogeneous parallel machine scenario, where each technician working at the production bench has a different production rate, S_i. A non-identical parallel machine configuration case was also studied by [29] with a

production configuration that forms batches of orders. In a non-identical parallel machine setting, the processing time of a job depends on the specific machine to which it is assigned (denoted as P_{jk}), reflecting real-world manufacturing scenarios where machines possess varying capabilities, ages, or specialized tooling. In contrast, the parallel machine scenario adapted by [30] is the homogeneous parallel machines; each has the identical yield. A parallel machine production setup is also configured for the problem, in which orders cannot be split and must continuously be produced by the machine. Production scheduling-based Routing Problem (PRP) with time window and setup times was studied in [31] as an IPDS problem. This is another work utilizing an identical parallel machine configuration. Production of orders with a size of I is scheduled and every order has a time window constraint.

A make-to-order supply chain model utilizing the make-pack-route method was studied in [32] in a two-phase production scenario. Two-phase production involves granulating raw materials and the packaging of orders. Each process is conducted by facilities that are organized as parallel machine configurations. While routing, flexible order composition is allowed, and in-time delivery is ensured at the end. Order delivery is performed by identical vehicles $K > 0$. Travel time, and costs are minimized. To solve the problem, an iterative sequential scheduling method was employed, yielding numerical results. Also, [33] employed a make-to-order supply chain scenario, where identical parallel machines perform production. Each order is produced and delivered by vehicles in a time-sensitive manner, and vehicles return to the plant depot after delivery.

5.1.3. Flow Shop

In a flow shop machine environment, a multi-stage production system is studied. A unidirectional flow of the m products (jobs) having multiple operations performed through a predetermined route of machines are configured. At the end of the final operation, the product is finished and placed in the holding area. A flow shop is distinguished from a job shop environment, where a fixed route is present for each product. The flow of jobs for each machine is the same in a permutation flow shop for each product, whereas in a non-permutation flow shop, the route of material flow to the machines may change. In a permutation flow shop environment, an optimal schedule for processing jobs across all machines is determined and applied. This reduces the problem's complexity compared to other types of flow shop environments. In a flexible or hybrid workshop, independent sequencing of each job at different machines can be scheduled, increasing customization and realism. With this configuration, idle times are reduced, and overall output is increased, at the cost of increased problem complexity. In a hybrid flow shop, at least one production stage consists of other types of machine environments. A recent addition to customization is the distributed flow shop, which configures parallel flow shops across multiple facilities. Increasing the realism of the problem has been reported for distributed flow shop problems, and the need for effective solution methods is evident. A Q-learning-based metaheuristic algorithm and a learning-and-knowledge-assisted multi-population cooperative evolutionary algorithm were employed to obtain a solution [34].

A permutation flow shop production setting was also utilized, and products were combined into batches before delivery [35]. Product distribution was performed by multiple heterogeneous, capacitated vehicles that were allowed to take multiple trips. Total tour time and tardiness were minimized as the objective of the problem. [36] used dedicated vehicles with a permutation flow shop setting, in which a number of batches and their compositions are known before delivery. In this work, a two-step approach is utilized. In the first step, the optimal delivery routes and departure times are calculated, and in the second step, the delivery cost function is utilized to minimize the total delivery cost. [37] formulated a similar permutation flow-shop problem for the dairy production industry and solved it using nonlinear programming.

5.1.4. Job Shop

A job shop machine environment is characterized by highly flexible production and highly customized end products, with generally low-volume production. Unlike a flow shop, production does not need to follow the same job sequence at each machine. Flexible flow shops and job shops are differentiated by the fact that the sequence of the flow is the same in a flow shop, but assignments at each machine may vary, whereas in a job shop, the sequence of jobs may also change.

A job shop configuration for the primary aluminum production process is adopted in [38], in which the various production stages are modeled as a job shop environment. The introduction of temporal constraints and limited temporary storage capacities yields new insights into the classical job shop scheduling problem. This configuration is extended in [39] by incorporating green constraints to minimize both total completion time and total carbon emissions. Recent studies have explored evolved variants of the job shop model, including the flexible job shop and the multi-facility or distributed job shop. In [40], flow shop and flexible job shop environments are examined within a three-stage process comprising design, production, and distribution scheduling under time constraints. A flexible job shop model is employed in [41] to represent the production scheduling phase F_1 in an integrated supply chain context. This approach enables optimized job sequencing and resource allocation across multiple machines, allowing flexibility in assigning operations to alternative machines. Moreover, an increasing number of multi-facility flow shop configurations have been studied to address research gaps in integrated production and distribution scheduling (IPDS) problems.

Open shop configuration is similar to job shop configuration, as there is a process flow for each product between machines. However, in the former configuration, each process stage or operation can be performed on any available machine. Additionally, the open shop process flow can also be altered.

5.2. Number of Products

The number of products demanded by the customer within the planning horizon is a key characteristic that distinguishes problems into single- or multiple-product types. In single-product scenarios, the entire production schedule is dedicated to a single good, manufactured on either identical or parallel machines with potentially heterogeneous processing times. The distribution schedule for a given customer order typically commences immediately upon completion of the required quantity. In contrast, multi-product problems introduce greater complexity. The production schedule must account for the sequencing of different items, where machines may be configured as dedicated lines for specific product types or as non-identical parallel processors. Consequently, the shipment for a customer order can begin only after production of all distinct product types in that order has been finalized.

In the article [42], demand is not treated as a continuous variable or forecast but as a discrete known set of n independent orders $J = \{J_1, J_2, \ldots J_n\}$ that the manufacturer has already received at the beginning of the planning horizon. Regardless of the order size, the model assumes every order is packaged into a single, standard-size pallet for delivery. This normalization of order quantity directly defines the distribution constraints; vehicle capacity is consequently measured not by total weight or volume, but as a fixed number C of orders (pallets) that a single vehicle can transport. The article [43] involves production scheduling and delivery of a single product with a lifespan constraint, with hard time windows for delivery. Similarly, [44] studies the scheduling of a single batch of production with identical processing times of the machines.

The work of [27] consists of a set of n jobs, where each job is associated with a specific customer, and customers may order multiple distinct jobs. This structure inherently creates multi-product scenarios, as jobs are processed on unrelated parallel machines with machine-dependent processing times and then delivered to multiple customer locations. The model by [45] is built around product differentiation. It explicitly defines the n orders as belonging

to g distinct product types. This type is a critical parameter that dictates essential processing characteristics; a job's type determines its specific processing time p_{it} and its energy consumption e_{it} at each manufacturing stage. This type-dependent product also governs the inventory system, as the warehouse maintains a specific quantity of on-hand stock I_t for each product type.

5.3. Number of Factories

In IPDS problems, the machine configuration fundamentally defines the shop floor environment of the production facilities. While in traditional production planning a single-factory system with parallel machines can be structurally analogous to a multi-factory system with a single machine, this equivalence does not hold in an IPDS context. The integration with distribution logistics means that each distinct combination of machine configuration and number of factories presents a unique problem class, necessitating a tailored modelling and solution approach.

Home Chemotherapy Delivery Problem (HCDP) was studied in [46], the factory corresponds to the hospital pharmacy, where chemotherapy drugs are produced. An optimal schedule is studied for balancing the inherent trade-off between production flexibility and the economic viability of the home chemotherapy service. [47] expands the scope of the IPDS problem setting by considering a multi-factory supply chain with parallel machines in each factory and immediate shipments to customers, thereby minimizing total production, distribution, and tardiness costs.

A single factory setting is also a focus of the literature. This focus, however, limits the applicability of findings to centralized supply chains and bypasses the complexities of multi-site coordination. [48] configures a single factory setting with parallel machines and distributes products with shelf life to customers within hard time windows. [49] investigates an IPDS problem where orders first undergo a single operation on one of several identical parallel machines. Upon completion, a limited number of vehicles deliver the consolidated customer orders within time windows. Vehicle energy consumption is modelled as a function of the load size.

5.4. Depot Usage

The production sub-problem of the IPDS problem ends in either transferring to a depot or directly shipping to customers. Product transfers can be performed to a central depot or multiple depots. For this classification element, a dedicated storage process inside the factories is also considered a depot. In these problems, the mathematical model does not include the transfer process of the products from the factory to the depot inside the factory. In the direct shipment case, products are shipped directly to customers. The factory's inventory is considered limitless, and the transfer of goods after production is assumed to be instantaneous.

In the study of [26] a single production site, which also serves as the single depot, is configured. In their formulation, completed jobs are held in inventory adjacent to the production machine, and the fleet of vehicles is dispatched from this depot to deliver goods and subsequently returns to the same location. Similarly, [24] utilizes a single depot concept for distribution but distinctly separates the production and distribution origins. Orders are produced on a supplier's single production line and then transferred to a third-party logistics (3PL) provider, from whose site distribution transporters depart at fixed times to reach customers. In contrast, [39] addresses a more complex configuration involving multiple depots integrated with a distributed production environment. Here, production occurs across several geographically dispersed factories, each functioning as a potential depot. This study uniquely incorporates a shared transportation resource (STR) strategy, enabling vehicles to execute delivery tasks originating from any factory depot. This enables a flexible and agile distribution system across the network. [50] considers a permutation flow shop machine configuration with sequence-dependent setup time (SDST) vehicle routing issues is proposed to reduce lateness and batch distribution costs. A single depot model is

considered where the production plant also serves as the origin point for distribution vehicles, which return after deliveries.

5.5. Distribution Characteristics

The IPDS sub-problem for the distribution characteristics encompasses vehicle type, number of vehicles, and tour count, which are specific to the problem setting. The number of vehicles may be a single vehicle, multiple vehicles, or a combination of both, depending on the transportation requirements. A 3PL provider is also considered to have multiple vehicles if the vehicles are involved in a detailed distribution schedule. It is marked as N/A if vehicles are not detailed in the study. If vehicle fleets, vehicle counts, or multi-stop vehicle tours are not explicitly modelled in the analyzed study, each characteristic is marked as N/A. [51] utilizes distribution as a discrete event that has a fixed cost and a capacity limit. [52] configures distribution-as-a-service to be purchased from a third-party logistics (3PL) provider and does not include any details about the vehicle or distribution plan. [53] models the distribution as a per-unit transportation cost from a plant to a distribution center.

In the article [38], bulk carriers are used with different properties, depending on the goods being carried and the shipping destinations, suggesting that a heterogeneous type of carrier is present. Vehicle or tour count in the problem is not constrained; goods are transported from different sites. [54] utilizes distribution with homogeneous vehicles and unlimited vehicle count, constrained by the total cost of the process. The number of tours is not limited. Customer demand is not mixed; each customer's demand is shipped directly as a batch.

[55] deals with VRP as part of IPDS, utilizing a fleet of heterogeneous vehicles. Vehicles show different attributes based on the type mentioned in the problem. Each type of vehicle varies in terms of capacity Q^k, drop cost φ^k, and direct delivery cost h_j^k. Adding a layer of complexity to the IPDS problem, the solution algorithm must choose a type of vehicle for delivery. [103] does not involve classical VRP features; instead, the distribution center and transport mode are determined. Transport mode refers to road, rail, or waterway transport, which implies heterogeneous vehicles are available. The cost of transportation and the speed profile vary depending on the chosen mode. Direct shipment to the customers, one at a time, with batches assigned.

5.6. Temporal Characteristics

The Number of Periods and the Time Window are temporal characteristics for IPDS problems that define the problem's planning horizon and customer service constraints. The number of periods indicates whether the problem is modelled as a static plan or divided into multiple discrete time buckets. The time window is an operational-specific interval within which a customer's order must be delivered. These windows can be strict (hard) or flexible (soft), with associated penalties for early or late deliveries. The presence of time windows links production completion times to the distribution in terms of feasibility and cost. Considering time windows in the mathematical model significantly increases problem complexity, as production schedules must be coordinated with vehicle routes to ensure timely delivery, moving beyond minimizing cost or makespan to providing service objectives.

The study of [33] configures a single-period problem with a static plan. The model investigates vehicle routing with time windows and aims to deliver items within time windows $[l_i, u_i]$ to minimize the distribution costs. Soft time windows are applied, as vehicles are allowed to deliver products to customers outside the time windows, incurring earliness and tardiness penalties. [24] addresses a single-period problem. In this study, explicit hard time windows are used as due dates for the earliest and latest delivery times. Service level as an objective function is maximized by minimizing the weighted number of late X orders U_j^X. [56] states that the start of production is the time all customer orders are received, implying a static model or a single-period problem. Hard time windows are applied together with soft time windows. Hard earliest arrival time e_k denotes the time vehicle is allowed to

arrive after. If the vehicle arrives after the soft latest arrival time la_k, a delayed cost is incurred. Hard upper limit up_k is the final deadline for the delivery to be completed.

6. Solution Methods of the IPDS Problem

6.1. Objective Function Characteristics

The objective function of the IPDS problem can be modelled with cost-based, service-based, quality-based, and green elements-based elements. A problem may contain one or a few objective characteristics together. Cost-based objectives include minimizing production, distribution, and storage costs, as well as temporal costs associated with the earliness or tardiness of vehicle arrival at the customer site. Service-based objectives primarily focus on customer satisfaction and supply chain responsiveness, often involving minimizing makespan. To address product integrity, quality-based objectives aim to reduce spoilage or damage by minimizing the time products spend in transit or under specific environmental conditions. Increasingly, modern IPDS models also integrate green elements, aiming towards sustainable logistics. These objectives include minimizing carbon emissions and fuel consumption from distribution vehicles, reducing overall energy use in production, and optimizing waste generation throughout the integrated system. The IPDS problem often manifests as a complex multi-objective optimization, requiring decision-makers to balance the inherent trade-offs among economic efficiency, service quality, and environmental savings.

In the article [33], the total distribution cost, which is composed of transportation and earliness/tardiness penalty costs, is minimized. This is a cost-based objective; additionally, earliness and tardiness are monetized. Explicit consideration of service involves a multi-objective problem aimed at delivering within the customer's time windows. Similarly, [29] also minimizes delivery costs and includes tardiness of each job T_j calculated as the difference between delivery time and its due date d_j. The paper does not include a green quality objective. [56] minimizes total distribution ccosts whileminimizing delays. Furthermore, the customer's purchasing probability is calculated based on the product's useful life sl_p, and its quality reduction point QRP_p, modeling the linear de, y of perishable product value over time. This illustrates a quality-based objective decision, rendering the problem a multi-objective study with three distinct objective approaches. [57] defines an environmental objective that aims to minimize vehicle carbon emissions and reduce fuel consumption. Likewise, this study minimizes distribution and fixed and variable fuel costs. Delivery tardiness and customer dissatisfaction with delivery outside prioritized time windows are also minimized as two distinct service-based objectives.

6.2. Solution Approaches

IPDS problems, as stated in the previous sections, are highly complex, rendering them unsuitable for exact methods on medium- to large-scale problems. The solutions to this NP-hard problem can be systematically categorized into four primary methodologies, each offering a distinct balance between computational effort and solution quality. Exact solution methods, such as branch-and-bound, dynamic programming, and mixed-integer linear programming (MILP), solved with standard solvers, are guaranteed to find the optimal solution [58], [59]. However, their exponential computational complexity renders them intractable for all but the most simplified problem instances. To address larger, more realistic problems, heuristic methods are employed [60], [61]. These are problem-specific rules and constructive procedures (e.g., dispatching rules or greedy algorithms) that generate feasible solutions with very low computational overhead, though without any guarantee of optimality. Metaheuristics offer a higher-level strategy for the solution search process. Common metaheuristics applied to IPDS include genetic algorithms (GA), tabu search (TS), and simulated annealing (SA), which are designed to escape local optima and find near-optimal solutions [62], [63], [64]. Finally, hybrid metaheuristics combine the strengths of two or more approaches, most frequently integrating a metaheuristic with a local search or exact method to refine solutions for superior overall performance [65].

The study, [66] proposes a MILP model as an exact solution method for the problem. It uses a rolling-horizon heuristic with accelerated Benders decomposition as a hybrid metaheuristic. [67] used mixed integer programming (MIP) method to solve 2592 test instances with GAMS/CPLEX software. 1283 of the instances are solved optimally within the two-hour test limit. A simple heuristic method is employed to generate high-quality initial solutions, and it also uses local search mechanisms within its main algorithm. The memetic algorithm (MA) is the main contribution of the paper to the literature, defined as the integration of an evolutionary algorithm with a local search algorithm. The obtained results for test instances of MIP and MA are compared. Using the Gurobi solver, [68] formed and obtained exact solutions with a monolithic-batch-centric, continuous-time MILP model. Heuristics are not required with the integrated production and pipeline distribution problem. Relaxed simplified programming (RSP) is developed and used with a MILP model in [69] and used to solve small-scale instances with the CPLEX solver. The paper proposes a heuristic solution procedure to address the primary issue. This includes heuristic algorithms to generate the initial solution. It also uses seven different neighborhood structures. The main algorithm is designed within the SA framework. A hybrid metaheuristic, limited integrated simulated annealing (LISA), combines the SA framework with various custom heuristic neighborhood structures to obtain the solution search. [70] modelled the problem as an MIP model. It is used to solve small-scale problems using the epsilon-constraint method and is solved with Gurobi. A hybrid metaheuristic, the self-adapted Gaussian mutation-based arithmetic optimizer algorithm (SGMAOA), is employed in this paper and benchmarked against test instances using several other metaheuristics. This is an advanced version of the Arithmetic Optimizer Algorithm (AOA). It modifies the standard AOA by integrating several new operators, including an adaptive Gaussian mutation operator and a multi-source information iteration strategy.

7. Classification Framework

To systematically analyze and compare the problem settings of studies on IPDS, a structured classification scheme is essential. An effective classification scheme is also necessary to identify research gaps in the literature and discern research trends in the state of the art. Furthermore, such a classification allows for a clearer understanding of the assumptions, constraints, and operational details that define different IPDS problems, and facilitates the comparison of solution approaches. The classification framework is composed of two layers:

- Classification based on problem settings.
- Classification based on objective function, environmental considerations, and solution approaches

With this methodology, the characteristics of IPDS studies published after 2010 are intended to be categorized and distinguished. Classification of problem characteristics of the selected articles is given in Table A**.1. A** proposed taxonomy for classifying IPDS literature. Solution methods are investigated and summarized in Table A.2. **A** proposed taxonomy for classifying IPDS research based on objective function properties, environmental considerations, and solution approaches.

8. Analysis of Current State of IPDS Problems, Research Trends, and Gaps

8.1. Analysis of Problem Characteristics and Research Trends

8.1.1. Machine Configuration

The frequency distribution of machine configurations within IPDS research reveals a distinct prioritization between model tractability and industrial representation. The results of the analysis are given in Table 4. Frequency of usage of machine configurations in IPDS problems.

Table 4. Frequency of usage of machine configurations in IPDS problems.

Production Machine Configuration	Count	Percent
Distributed Flow Shop	1	1.47
Distributed Flow/Flexible Job Shops	1	1.47
Flexible Flow Shop	3	4.41
Flexible Job Shop	1	1.47
Flow Shop	3	4.41
Hybrid Flow Shop	3	4.41
Identical Parallel Machines	1	1.47
Job Shop	3	4.41
Non-Identical Parallel Machines	1	1.47
Parallel Machines	15	22.06
Permutation Flow Shop	4	5.88
Single Machine	31	45.59
Unrelated Parallel Machines	1	1.47
Grand Total	**68**	**100.00**

The dominance of the single-machine (45.59%) configuration indicates that isolating model complexities is preferred for the application of exact solution methods and the development of new heuristic methods. This is an academic trade-off of IPDS problems, as a realistic integrated process contains more complex production machine configurations. Parallel machines (22.06%) and their variants (4.41%) are the second-most frequent machine configuration in IPDS research, while flow shop machines (22.06%) and their variants collectively account for nearly a quarter of the total. In contrast to these machine configurations, job shop configurations and their variants are the least explored machine configurations (7.35%), highlighting a critical research gap. This indicates the field has not yet fully grappled with the combinatorial challenges of simultaneous job routing, machine assignment, and delivery scheduling.

The substantial body of work on parallel machine and flow shop configurations demonstrates a conscious escalation of complexity from the single-machine foundation. Researchers are methodically adding features, such as multiple production stages or parallel workstations, before confronting the full complexity of flexible routing. Therefore, the current state of the IPDS literature is characterized by a solid methodological foundation built on simplified models, with the pressing future challenge being the translation of these advances to more complex, realistic machine configurations that remain on the periphery of current study.

8.1.2. Factory and Product Configuration

The data for factory multitude and product configuration is analyzed and given in Table 5.

Table 5. Frequency of preference for a multitude of factories and products in IPDS problems.

Factory/Product Configuration	Count	Percent
Single Factory	43	63.24
Multiple Products	20	29.41
Single Product	23	33.82
Multiple Factories	25	36.76
Multiple Products	19	27.94
Single Product	6	8.82
Grand Total	**68**	**100.00**

The data indicate that a single factory environment (63.24%) is the primary focus of the research effort in the IPDS problem, as well as multiple factories. This indicates that previous efforts have focused on solving the core logistical integration of the problem before escalating to the multiple production facility dimension. Similar to a single-machine environment, the dominance of a single factory setting reflects a deliberate preference for simplifying the problem rather than increasing computational complexity.

Furthermore, the product scope reveals a balanced split between single-product (33.82%) and multiple-product (29.41%) settings for the single factory. However, in the multiple factory environment, the split is more pronounced, with single products (8.82%) and multiple products (27.94%) being more prevalent. The data suggests that the challenges of multi-site production coordination and its interaction with distribution networks are addressed through the diverse product demand, enabling the development of effective solution methods for the highly complex problems.

8.1.3. Depot Configuration

Direct shipment and the use of a depot or multiple depots are analyzed and presented in Table 6.

Table 6. Frequency of direct shipment and depot utilization in IPDS problems.

Depot Configuration	Count	Percent
Direct Shipment	43	63.24
Multiple Depots	11	16.18
Single Depot	14	20.59
Grand Total	**68**	**100.00**

The frequency of depot configuration in IPDS problems indicates a heavily focused effort on direct shipment (63.24%), demonstrating that the field heavily simplifies the distribution component to prioritize the analysis of production-distribution integration. This model, which ships completed jobs to customers immediately without intermediate consolidation, effectively eliminates the complex routing and inventory-allocation decisions inherent in multi-echelon distribution.

8.1.4. Distribution Characteristics

Distribution characteristics are collected and represented in relation to one another in Table 7. The data on distribution characteristics reveal a strong preference within the field for modeling homogeneous vehicle fleets in multi-vehicle settings (55.88%). Heterogeneous vehicles account for 19.2% of the grand total; this data suggests that foundational models in the IPDS field prioritize simplicity and tractability. Homogeneous fleet models are mathematically less complex, allowing researchers to focus on core operational challenges, such as routing and scheduling, without the added complication of managing different vehicle types in terms of capacity and cost. Homogeneous, multiple vehicle models indicate a focus on establishing robust solutions for fleet coordination and makespan minimization. Single-vehicle problems represent a small minority (11.76%) of the research. For homogeneous fleets, multi-tour and single-tour models are equally represented (27.94% each). This indicates that both operational paradigms are of significant interest. The heterogeneous vehicle category shows a preference for multi-tour (13.24%) over single-tour (5.88%) operations. This implies that when researchers tackle the complexity of a heterogeneous fleet, they are often simultaneously addressing the added complexity of multi-tour operations. The nearly even split between single-tour and multi-tour operations across all categories indicates a healthy balance between foundational work on solution methods and more complex scheduling problems. The most significant research gap and opportunity for future work lies in the heterogeneous fleet domain, which is critically important for real-world applications but remains under-explored compared to its homogeneous

counterpart. A small number of IPDS publications that have not specified distribution characteristics (11.76%) integrate production and distribution, focusing on production characteristics and solution methods.

Table 7. Distribution characteristics frequency for each combination of characteristics.

Distribution Characteristics	Count	Percent
Heterogeneous	**13**	**19.12**
Multiple Vehicle	**13**	**19.12**
Multi-tour	9	13.24
Single-tour	4	5.88
Homogeneous	**47**	**69.12**
Multiple Vehicle	**38**	**55.88**
Multi-tour	19	27.94
Single-tour	19	27.94
Single Vehicle	**8**	**11.76**
Multi-tour	5	7.35
Single-tour	3	4.41
Single Vehicle/Multiple Vehicle	**1**	**1.47**
Multi-tour	1	1.47
N/A	**8**	**11.76**
N/A	**8**	**11.76**
N/A	8	11.76
Grand Total	**68**	**100.00**

8.1.5. Temporal Characteristics

The frequency of usage of temporal characteristics is analyzed and presented in Table 8.

Table 8. Temporal characteristics frequency for each combination.

Temporal Characteristics	Count	Percent
Hard time windows	**24**	**35.29**
Many periods	4	5.88
Single period	20	29.41
N/A	**39**	**57.35**
Many periods	2	2.94
Single period	**37**	**54.41**
Soft time windows	**5**	**7.35**
Many periods	1	1.47
Single period	**4**	**5.88**
Grand Total	**68**	**100.00**

The frequency of including temporal characteristics data shows that the majority of publications (57.35%) are categorized as "N/A" for time windows. This suggests that a significant portion of IPDS research focuses on addressing the fundamental spatial routing and resource allocation problem. Within these, an overwhelming majority of models (54.41%) are single-period with no time windows, and, across all characteristics, single-period (89.71%) is the clear standard among IPDS problems. This confirms that IPDS is primarily studied as a tactical/operational planning problem for a single time block. The field is largely concerned with optimizing a single time window of the system. The high frequency of hard time windows (35.29%) suggests that the field

often prioritizes modeling mandatory service limits. The under-representation of soft time windows and multi-period planning indicates significant opportunities for future research. Advancing the field will likely involve developing more sophisticated models that incorporate multi-day or multi-period operational scheduling and constraint flexibility of logistic systems with soft time windows.

8.2. Analysis of Solution Methods and Research Trends

8.2.1. Objective Function Characteristics

The objective function category application frequency is represented in Figure 4.

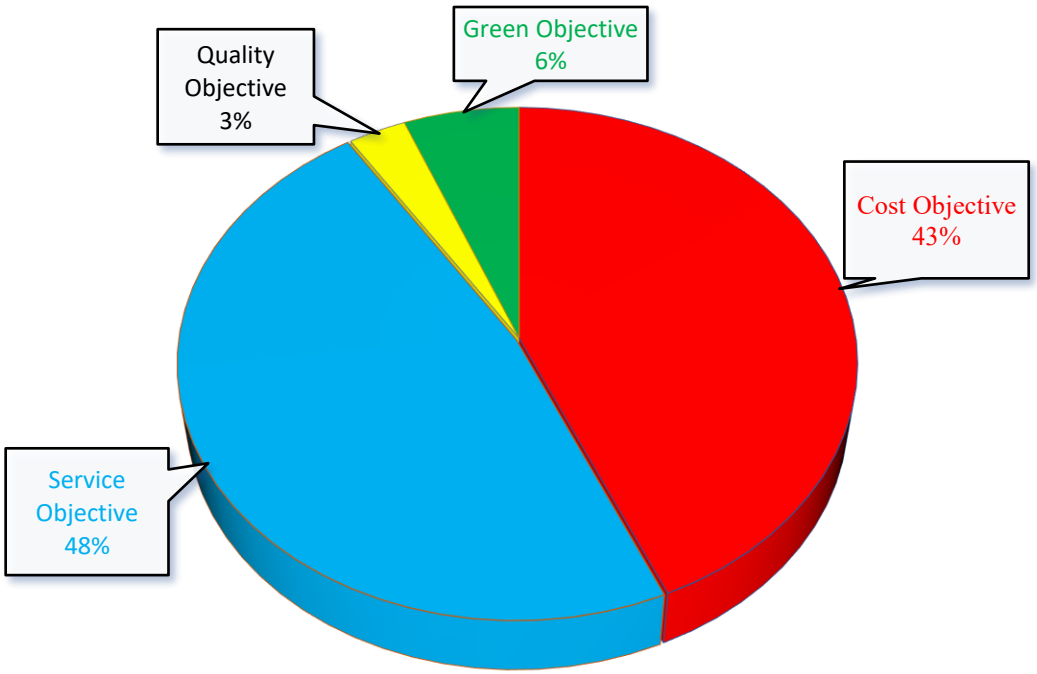


Figure 4. Pie chart of the frequency of usage (%) of objective functions in IPDS problems.

The analysis of 68 articles reveals a descriptive structure of objective functions in the scope of IPDS research. A significant finding is that a decent number of articles (41.18%) were observed to be integrating two or three categories of objective function elements. This is a critical evolution in the field, moving beyond single-dimensional cost-minimization paradigms to satisfy real-world operational goals. The remaining studies (58.82%) that focus on single objectives likely represent foundational work or contexts in which a primary driver is the dominant factor. For example, makespan minimization may be the company's top priority, while costs associated with the operation may be a secondary objective that need not be optimized. Cost (43.43%) and service (47.47%) objectives are the two most common objective function choices in the IPDS literature. Similarly, they are considered simultaneously as two categories that may work in opposite directions and need to be balanced. Green (6.06%) and quality (3.03%) are the least utilized objective types, leaving a potential research opportunity, especially in the fields of sustainability and customer satisfaction. The strong showing of the multi-objective category establishes it not as a niche area, but as a central and necessary focus for future research aimed at generating practically viable and managerially relevant scheduling solutions.

8.2.2. Solution Approaches

Analysis of solution methods of IPDS problems yields balanced results for the chosen methodology of solution and the results are given in Table 9.

Table 9. Solution methodologies applied in IPDS problems.

Solution Method	Count	Percent
Exact Solution	47	37.90
Heuristic	18	14.52
Metaheuristic	25	20.16
Hybrid Metaheuristic	34	27.42

The exact solution (37.90%) is the standard solution method as expected. This is because the effectiveness of heuristic, metaheuristic, or hybrid metaheuristic methods is typically evaluated in terms of a relative gap or optimality gap compared to the best feasible or optimal solution. Additionally, for small-scale or simplified problems, optimal solutions can be obtained using exact solution methods. When an optimal solution cannot be obtained within a reasonable time, the best possible solution provided by the optimization software is used for comparison. Hybrid metaheuristics (27.42%) are the most common non-deterministic solution method for the IPDS problem. This method is essentially designed to overcome the limitations of pure metaheuristics [116]. Their dominance suggests that the community recognizes the need for sophisticated, tailored algorithms to solve the IPDS problem effectively and efficiently. Among hybrid metaheuristic methods, memetic algorithms (12 out of 34) are the most widely used for the IPDS problem. Metaheuristics (20.16%) are also widely applied to obtain solutions to the IPDS problem within a reasonable timescale. Among metaheuristic algorithms, the genetic algorithm (9 out of 25) is the most common in the articles. When combined, hybrid metaheuristics and metaheuristic approaches account for nearly half (47.58%) of all applied solutions. This data suggests that researchers are less successful with simple heuristics (14.52%) than with advanced heuristic methods. This finding is significant and aligns with theoretical expectations. The complex nature of IPDS problems is not well-suited to basic heuristics, which typically fail to achieve high optimality gaps. This trend is a significant indicator of the field, as it has matured beyond mere feasibility and is now focused on developing algorithms that can reliably deliver high-performance, practical solutions for industrially relevant problem scales.

9. Conclusions

This systematic review synthesizes the progression of IPDS research from 2010 to 2025, analyzing the evolution of both problem characteristics and solution methodologies. Our analysis reveals a clear trajectory: the field has increasingly focused on complex, realistic problem settings. Correspondingly, solution methods have evolved from exact algorithms for limited-scale problems to the current dominance of metaheuristics and hybrid metaheuristics, which provide pragmatic and effective approaches for tackling this NP-hard class of problems.

Despite these advancements, a significant gap persists between theoretical models and the dynamic, data-rich environments of modern Industry 4.0 supply chains. To bridge this gap, future research should prioritize the following areas:

- Job Shop Configurations: The job shop machine configuration and its variants remain the least explored. This area presents substantial opportunities to apply and develop advanced solution methods to manage its inherent complexity.

- Multi-Facility Production: Models involving multiple production facilities (e.g., distributed flow shops) are often avoided due to escalating complexity. Research into multi-facility systems, with their diverse machine configuration and product multitude combinations, is a critical and open avenue.
- Heterogeneous Fleets: The integration of heterogeneous vehicle fleets with varying properties remains a notable gap. The absence of a clear trend in the use of such fleets across different problem settings indicates a significant, unexplored dimension of realism.

- Multi-Period Planning Horizons: Realistic operational schedules typically span multiple periods; a feature largely absent from existing IPDS literature. The incorporation of multi-period planning is a crucial research direction for enhancing the practical applicability of models.
- Soft Time Windows: While the consideration of soft time windows with earliness and tardiness penalties is a growing topic, it warrants further in-depth investigation to better reflect real-world logistics constraints.
- Solution Methodologies: Although metaheuristics are widely studied, no single dominant method has emerged within each algorithmic category. This suggests a vast, untapped potential for exploring new algorithmic combinations and tailoring them to problems of varying complexity. The enduring challenge is to develop methods that yield near-optimal solutions within reasonable computational timeframes.
- Advances in Exact Methods: Progress in both algorithmic techniques and computing technology may eventually enable the application of exact methods to medium- and large-scale problems, representing a promising long-term research frontier.

By addressing these gaps, the IPDS field can significantly enhance its practical impact, providing agile, responsive decision-support tools that effectively manage the complexities of contemporary global supply chains.

Declaration of Competing Interest

No conflict of interest was declared by the authors.

Authorship Contribution Statement

Onur Türel: Survey, Analysis and Writing
Abdül Kadir Görür: Review and Supervision
Ferda Can Çetinkaya: Review and Supervision

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Appendices

Table A.1. A proposed taxonomy for classifying IPDS literature.

Reference Number	Year	Machine Type	Product	Factory	Depot Usage	Vehicle Type	Vehicle Count	Tour Count	Number of Periods	Time Window
[69]	2025	Single Machine	Multiple Products	Single Factory	Direct Shipment	Heterogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[66]	2025	Single Machine	Multiple Products	Multiple Factories	Multiple Depots	Heterogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[68]	2025	Single Machine	Single Product	Multiple Factories	Multiple Depots	N/A	N/A	N/A	Single period	N/A
[40]	2025	Distributed Flow/Flexible Job Shops	Multiple Products	Multiple Factories	Direct Shipment	Homogeneous	Multiple Vehicle	Multi-tour	Single period	N/A
[46]	2024	Identical Parallel Machines	Single Product	Multiple Factories	Single Depot	Homogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[41]	2024	Job Shop	Multiple Products	Single Factory	Single Depot	Homogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[49]	2024	Parallel Machine	Multiple Products	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[48]	2024	Parallel Machines	Single Product	Single Factory	Single Depot	Homogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[44]	2024	Single Machine	Single Product	Single Factory	Single Depot	Homogeneous	Single Vehicle	Multi-tour	Single period	N/A
[70]	2024	Job Shop	Multiple Products	Multiple Factories	Multiple Depots	Heterogeneous	Multiple Vehicle	Multi-tour	Many periods	Hard time windows
[71]	2024	Single Machine	Single Product	Multiple Factories	Multiple Depots	Homogeneous	Multiple Vehicle	Multi-tour	Single period	N/A
[34]	2024	Distributed Flow Shop	Multiple Products	Multiple Factories	Multiple Depots	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[67]	2024	Single Machine	Single Product	Multiple Factories	Direct Shipment	Homogeneous	Single Vehicle	Multi-tour	Single period	N/A
[72]	2024	Single Machine	Single Product	Multiple Factories	Direct Shipment	Homogeneous	Single Vehicle/Multiple Vehicle	Multi-tour	Single period	N/A
[73]	2024	Multiple Product	Single Product	Single Factory	Direct Shipment	Heterogeneous	Multiple Vehicle	Multi-tour	Single period	Soft time windows
[74]	2023	Hybrid Flow Shop	Multiple Products	Single Factory	Single Depot	Homogeneous	Multiple Vehicle	Multi-tour	Single period	N/A
[75]	2023	Parallel Machines	Multiple Products	Single Factory	Single Depot	Heterogeneous	Multiple Vehicle	Multi-tour	Single period	Soft time windows
[76]	2023	Hybrid Flow Shop	Multiple Products	Multiple Factories	Direct Shipment	Homogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows

Table A.1. cont.

[45]	2023	Flow Shop	Multiple Products	Multiple Factories	Single Depot	Heterogeneous	Multiple Vehicle	Single-tour	Single period	Soft time windows
[77]	2023	Flexible Job Shop	Multiple Products	Multiple Factories	Multiple Depots	Homogeneous	Multiple Vehicle	Multi-tour	Single period	N/A
[50]	2022	Permutation Flow Shop	Multiple Products	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[26]	2022	Single Machine	Multiple Products	Single Factory	Single Depot	Homogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[24]	2022	Single Machine	Multiple Products	Single Factory	Single Depot	Homogeneous	Multiple Vehicle	Single-tour	Single period	Hard time windows
[78]	2022	Single Machine	Multiple Products	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[33]	2021	Parallel Machines	Multiple Products	Single Factory	Single Depot	Homogeneous	Multiple Vehicle	Single-tour	Single period	Soft time windows
[56]	2021	Flexible Flow Shop	Multiple Products	Single Factory	Single Depot	Heterogeneous	Multiple Vehicle	Single-tour	Single period	Hard time windows
[79]	2021	Hybrid Flow Shop	Single Product	Multiple Factories	Direct Shipment	Heterogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[80]	2021	Parallel Machines	Multiple Products	Multiple Factories	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[29]	2021	Non-Identical Parallel Machines	Single Product	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[57]	2020	Single Machine	Single Product	Single Factory	Direct Shipment	Heterogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[81]	2020	Permutation Flow Shop	Multiple Products	Single Factory	Direct Shipment	Homogeneous	Single Vehicle	Multi-tour	Single period	N/A
[82]	2020	Parallel Machines	Multiple Products	Multiple Factories	Multiple Depots	N/A	N/A	N/A	Many periods	N/A
[83]	2020	Single Machine	Multiple Products	Multiple Factories	Direct Shipment	Heterogeneous	Multiple Vehicle	Multi-tour	Single period	N/A
[84]	2019	Parallel Machines	Multiple Products	Multiple Factories	Single Depot	Homogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[85]	2019	Parallel Machines	Multiple Products	Multiple Factories	Direct Shipment	N/A	N/A	N/A	Single period	Hard time windows
[86]	2019	Parallel Machines	Multiple Products	Multiple Factories	Single Depot	Homogeneous	Multiple Vehicle	Multi-tour	Single period	N/A
[87]	2018	Single Machine	Single Product	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[88]	2018	Flexible Flow Shop	Single Product	Single Factory	Multiple Depots	N/A	N/A	N/A	Many periods	N/A
[89]	2018	Parallel Machines	Single Product	Single Factory	Direct Shipment	Homogeneous	Single Vehicle	Single-tour	Single period	N/A
[90]	2018	Single Machine	Single Product	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A

Table A.1. cont.

[91]	2018	Single Machine	Multiple Products	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[92]	2018	Permutation Flow Shop	Multiple Products	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Multi-tour	Single period	N/A
[93]	2018	Flow Shop	Multiple Products	Multiple Factories	Direct Shipment	Homogeneous	Multiple Vehicle	Multi-tour	Many periods	Soft time windows
[94]	2018	Parallel Machines	Multiple Products	Multiple Factories	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[47]	2018	Parallel Machines	Multiple Products	Multiple Factories	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[95]	2018	Flow Shop	Multiple Products	Single Factory	Multiple Depots	Heterogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[55]	2017	Parallel Machines	Multiple Products	Single Factory	Direct Shipment	Heterogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[37]	2017	Permutation Flow Shop	Single Product	Single Factory	Direct Shipment	Heterogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[96]	2017	Single Machine	Single Product	Single Factory	Single Depot	Homogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[97]	2017	Single Machine	Multiple Products	Single Factory	Direct Shipment	Homogeneous	Single Vehicle	Multi-tour	Single period	N/A
[98]	2016	Single Machine	Single Product	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[99]	2016	Flexible Flow Shop	Single Product	Single Factory	Multiple Depots	Homogeneous	Multiple Vehicle	Single-tour	Many periods	Hard time windows
[100]	2016	Single Machine	Single Product	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[101]	2016	Single Machine	Single Product	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Multi-tour	Single period	N/A
[102]	2015	Parallel Machines	Multiple Products	Multiple Factories	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	Hard time windows
[103]	2015	Single Machine	Multiple Products	Single Factory	Direct Shipment	Homogeneous	Single Vehicle	Multi-tour	Single period	N/A
[104]	2015	Single Machine	Multiple Products	Single Factory	Direct Shipment	N/A	N/A	N/A	Many periods	Hard time windows
[54]	2015	Single Machine	Multiple Products	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[38]	2015	Job Shop	Multiple Products	Multiple Factories	Direct Shipment	Homogeneous	Multiple Vehicle	Multi-tour	Single period	Hard time windows
[105]	2015	Single Machine	Single Product	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[106]	2015	Single Machine	Single Product	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Multi-tour	Single period	N/A
[43]	2014	Single Machine	Single Product	Single Factory	Direct Shipment	Homogeneous	Single Vehicle	Single-tour	Single period	Hard time windows

Table A.1. cont.

[27]	2014	Unrelated Parallel Machines	Single Product	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Multi-tour	Single period	N/A
[42]	2014	Single Machine	Single Product	Single Factory	Direct Shipment	Homogeneous	Multiple Vehicle	Single-tour	Single period	N/A
[53]	2013	Parallel Machines	Multiple Products	Multiple Factories	Multiple Depots	N/A	N/A	N/A	Many periods	Hard time windows
[107]	2012	Single Machine	Single Product	Single Factory	Direct Shipment	Homogeneous	Single Vehicle	Single-tour	Single period	N/A
[52]	2010	Single Machine	Single Product	Single Factory	Direct Shipment	N/A	N/A	N/A	Single period	Hard time windows
[51]	2010	Single Machine	Single Product	Single Factory	Direct Shipment	N/A	N/A	N/A	Single period	N/A

Table A.2. A proposed taxonomy for classifying IPDS research based on objective function properties, environmental considerations, and solution approaches.

Reference Number	***Cost Objective***	***Service Objective***	***Quality Objective***	***Green Objective***	***Exact Solution***	***Heuristic***	***Metaheuristic***	***Hybrid Metaheuristic***
[69]	✓	✓			✓ (MILP)		✓ (LISA)	
[66]	✓				✓ (MILP + BD)			✓ (ABD)
[68]		✓		✓	✓ (MILP)			
[40]	✓	✓			✓ (MIP)			✓ (GA + Q-learning + VNS)
[46]	✓				✓ (MIP + LP)			✓ (LNS with Embedded LP)
[41]	✓	✓					✓ (GA and SA)	
[49]	✓	✓		✓	✓ (MIP)			✓ (MA)
[48]	✓				✓ (MILP + BD)		✓ (ILS)	✓ (MA)
[44]		✓				✓ (Optimal Approximation Algorithm)		
[70]		✓		✓	✓ (MIP)			✓ (Arithmetic Optimiser)
[71]	✓							✓ (MA)
[34]		✓		✓	✓ (MILP)		✓ (GA and Brainstorm and Grey Wolf operators)	✓ (Q-MEA)
[67]		✓			✓ (MIP)	✓ (MCW)	✓ (VNS)	

Table A.2. cont.

[72]		✓					✓ (VNS)	
[73]	✓	✓			✓ (MINLP)		✓ (MOEA/D)	✓ (KDCEA)
[74]		✓			✓ (MILP)			✓ (Improved MA)
[75]		✓	✓					✓ (MOEA + ALNS + Collaborative Mechanism)
[76]	✓				✓ (MIP)			✓ (GA + TS)
[45]		✓		✓	✓ (MILP)			✓ (Modified NSGA-II)
[77]		✓		✓	✓ (MINLP)			✓ (EMTLBO)
[50]	✓	✓			✓ (DP)		✓ (LS)	✓ (GA + LS)
[26]	✓	✓			✓ (MILP)			✓ (LMPSO)
[24]	✓	✓			✓ (MILP)			
[78]	✓				✓ (MILP)		✓ (NSGA-II)	✓ (HMOEA)
[33]	✓	✓			✓ (MILP)	✓ FFD		✓ (HMLO)
[56]	✓	✓			✓ (MILP)		✓ (MCHHA and NSGA-II)	✓ (MCHHA + LP-metric + Weighted Method)
[79]	✓	✓						✓ (Adaptive GA)
[80]	✓							✓ (LR + PSO)
[29]	✓				✓ (MILP)		✓ (GA)	✓ (Improved GA)
[57]	✓	✓	✓					✓ (MOPSO + NSGA-II + MOACO)
[81]		✓						✓ (MA)
[82]	✓				✓ (MILP)			
[83]		✓					✓ (RS and GA)	
[84]	✓	✓						✓ (ICA and IPSO)
[85]	✓						✓ (GA)	✓ (MA)

Table A.2. cont.

[86]	✓	✓			✓ (Bees Algorithm)	
[87]		✓	✓ (MIP)	✓ (TSA)	✓ (GA)	
[88]	✓	✓	✓ (SMIP)			
[89]		✓		✓ (Approximation Algorithms)		
[90]	✓		✓ (MILP + BBA)	✓ (GA)		
[91]	✓		✓ (MILP)		✓ (GA)	✓ (GA+OFSR+LS)
[92]		✓	✓ (MIP)		✓ (ICA)	✓ (I-ICA)
[93]	✓	✓			✓ (TS)	✓ (Two-Layer TS + PSO)
[94]	✓	✓	✓ (MILP)			✓ (MOEA/D + BA + LS)
[47]	✓	✓	✓ (MINLP)		✓ (WOA, IWOA, GA, MPC, PSO, SPSO)	
[95]	✓		✓ (MILP)		✓ (AIS and PSO)	
[55]	✓		✓ (MILP + CP)	✓ (Two-Phase Iterative)		
[37]	✓	✓	✓ (MINLP)			✓ (IPSO)
[96]	✓		✓ (MILP)		✓ (GA)	✓ (MA)
[97]	✓			✓ (FFD + Approximation)		
[98]		✓		✓ (Online Algorithms)		
[99]	✓	✓	✓ (Stochastic MIP)			
[100]		✓	✓ (DP)	✓ (Heuristic HA)		
[101]		✓	✓ (ILP)	✓ (LS)	✓ (TS)	✓ (MOAMP + AWS)
[102]	✓		✓ (MIP)			
[103]		✓	✓ (MIP)	✓ (Heuristic H)		

Table A.2. cont.

[104]	✓				✓ (Approximation Algorithm)		
[54]	✓	✓		✓ (DP)			
[38]	✓			✓ (MILP)	✓ (Relax and Fix)		✓ (Exact + Decomposition)
[105]	✓					✓ (I-ACO)	
[106]		✓		✓ (Polynomial-Time Algorithms)			
[43]		✓		✓ (MIP + BBA)	✓ (IH)	✓ (TS and ILS)	
[27]		✓				✓ (AC)	
[42]		✓		✓ (Polynomial-Time Algorithms)			
[53]	✓	✓	✓	✓ (MILP + Simulation)			
[107]		✓		✓ (Polynomial-Time Algorithms)	✓ (Online Algorithms)		
[52]	✓				✓ (Polynomial-time)		
[51]		✓		✓ (DP)	✓ (Online Algorithms)		

ABD: Accelerated Benders Decomposition, **AC:** Ant Colony, **ACO:** Ant Colony Optimization, **AIS:** Artificial Immune System, **ALNS:** Adaptive Large Neighborhood Search, **AWS:** Adaptive Weighted-Sum, **BA:** Bees Algorithm, **BBA:** Branch and Bound Algorithm, **BD:** Benders Decomposition, **EMTLBO:** Improved version of Teaching-Learning-Based Optimization, **FFD:** First-Fit Decreasing, **GA:** Genetic Algorithm, **HA:** Heuristic Algorithm, **Heuristic HA:** Polynomial-Time Heuristic, **Heuristic H:** Heuristic Method Using Enumeration and Shortest Path, **HMLO:** Hybrid Multi-Level Optimization, **HMOEA:** Hybrid Multi-objective Evolutionary Algorithm, **I-ACO:** Improved Ant Colony Optimization, **ICA:** Imperialist Competitive Algorithm, **IH:** Insertion Heuristic, **I-ICA:** Improved Imperialist Competitive Algorithm, **ILS:** Iterated Local Search, **IPSO:** Improved Particle Swarm Optimization, **IWOA:** Improved Whale Optimization Algorithm, **KDCEA:** Knowledge-driven Co-evolutionary Algorithm, **LISA:** Limited Integrated Simulated Annealing, **LMPSO:** An improved variant of PSO, **LNS:** Large Neighborhood Search, **LP:** Linear Programming, **LR:** Lagrangian Relaxation, **LS:** Local Search, **MA:** Memetic Algorithm, **MCW:** Modified Clarke & Wright Algorithm**,** **MCHHA:** Multi-Constraint Human Heuristic Algorithm, **MIP:** Mixed integer programming, **MILP:** Mixed integer linear programming, **MOACO:** Multi-Objective Ant Colony Optimization, **MOAMP:** Multi-Objective Adaptive Memory Programming, **MOEA:** Multi-Objective Evolutionary Algorithm, **MOEA/D:** Multi-Objective Evolutionary Algorithm Based on Decomposition, **MOPSO:** Multi-Objective Particle Swarm Optimization, **MPC:** Model Predictive Control, **NEH:** Nawaz, Enscore, Ham: **NSGA-II:** Non-dominated Sorting Genetic Algorithm II, **OFSR:** Optimal Fitness-based Selection Rule, **PSO:** Particle Swarm Optimization, **Q-MEA:** Q-learning-based Memetic Evolutionary Algorithm, **RS:** Random Search, **SA:** Simulated Annealing, **SPSO:** Standard Particle Swarm Optimization, **TS:** Tabu Search, **TSA:** Tabu Search Algorithm, **VNS:** Variable Neighborhood Search: **WOA:** Whale Optimization Algorithm