Integrated Process Planning, Scheduling, Due-Date Assignment and Delivery Using Simulated Annealing and Evolutionary Strategies

Onur Canpolat[1](✉), Halil Ibrahim Demir[1], and Caner Erden[2]

[1] Department of Industrial Engineering, Faculty of Engineering, Sakarya University, Sakarya, Turkey
{onurcanpolat,hidemir}@sakarya.edu.tr

[2] Department of International Trade and Finance, Faculty of Applied Science, Sakarya University of Applied Science, Sakarya, Turkey
cerden@subu.edu.tr

Abstract. Process planning, scheduling, and due date assignment functions are the three fundamental manufacturing functions. Traditionally, these functions were examined independently in production systems. The integrated communication of these functions is one of the most efficient ways to ensure high customer satisfaction, nonetheless, in the technological and competitive climate of today. Although these functions have been integrated in academic research over the past few decades, in practice, they are still generally performed sequentially and independently. Although limited research exists that integrates the three functions, this study introduces delivery as a fourth function. The objectives of this study are to make a significant contribution to the literature by demonstrating the integrated nature of four functions in manufacturing systems, with a view to increasing efficiency compared to traditional solutions. The study also seeks to investigate the impact of incorporating the delivery function. Customers are not viewed as being equal, as is the case with many of the other integrated studies that can be found in the literature; rather, each client is given special consideration. Each of the four job shops is unique and has a different number and location of customers. The study solves the complex problem by utilizing simulated annealing and evolutionary strategies algorithms. Both method-based and job shop-based comparisons are made, and the results show which methods perform better in each job shop. The results demonstrate that the integrated system offers an improvement of approximately 50% compared to independent systems. Furthermore, the study found that, across all four job shops, the evolutionary strategies (ES) outperformed simulated annealing (SA) in terms of results.

Keywords: Integrated process planning · scheduling and due-date assignment · simulated annealing · evolutionary strategies · delivery scheduling · distribution · transportation

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1 Introduction

Process planning, scheduling and due date assignment are three important functions. In classical planning, these three functions worked separately, even though they strongly affect each other [1]. This produces poor inputs for later phases and degrades the effectiveness of the overall solution. As a result, there can be significant losses in performance measures and shop floor (SF) productivity decreases. Besides, customers may become dissatisfied when given unnecessarily long due dates. Non-integrated production functions can cause losses across multiple different areas. Therefore, the integration of manufacturing functions is crucial. The integration will provide benefits such as the elimination of conflicting objectives between functions and the improvement of function-to-function communication, which will greatly enhance productivity, performance, and quality.

The task of integration is crucial but also challenging. Even the scheduling problem on its own is categorized as non-polynomial hard (NP-Hard) [2], which means exact solutions are only feasible for minor issues. When we expand our focus to encompass integrated problems, the difficulty level increases significantly. Research reveals that meta-heuristic algorithms are commonly used to solve analogous problems. This study applies simulated annealing and evolutionary strategies techniques tailored for this structure to evaluate their effectiveness against traditional approaches by comparing performance on global metrics.

This research defines the IPPSDDAD problem, which incorporates the delivery function as a fourth component into the integration of process planning, scheduling, and due date assignment functions. Initially, an independent structure with non-integrated functions is employed to assess performance with increasing levels of functional integration. While investigations on integrating three functions have been conducted in recent years and are documented in the literature, there remains significant potential for further inquiry within this domain. The integration of four functions constitutes an unprecedented area that warrants exploration and analysis by researchers.

The punishment of tardiness in scheduling has been approached in various ways in the literature, including punishing earliness and tardiness, maximum absolute lateness, or the number of tardy jobs. However, this research adopts a different approach by penalizing the sum of weighted tardiness, earliness, and due date-related costs. This approach is adopted to ensure that realistic due dates are set and to prevent unnecessary delays, particularly for important customers. The penalization of weighted tardiness aims to prevent late deliveries, which can lead to customer dissatisfaction, loss of customers, a damaged reputation, and price reductions. While tardiness has traditionally been the only aspect penalized, the present study recognizes that earliness can also be problematic in a JIT environment. Early deliveries can result in additional costs such as stock holding, storage, and spoilage, all of which are considered earliness costs. Therefore, the present study also penalizes weighted earliness to address this issue.

This research examines traditional job shop manufacturing and evaluates four distinct environments with varying numbers of jobs: 25, 50, 75, and 100. Additionally, the study acknowledges that customers may not carry equal significance. Many previous studies have neglected to consider customer weights while scheduling or establishing due dates. Important customers are also prioritized in the delivery phase. By privileging the important customer at every stage of production, this study aims to investigate how the integration of the four functions impacts the global solution in comparison to the non-integrated solution (SIRO-RDM). Additionally, the study examines the performance of the heuristic algorithms used and the effect of utilizing varying levels of customer importance on overall performance.

Section 2 will provide by giving an overview of the sub-problems explored in existing literature, followed by describing the methods and modeling used in Sects. 3 and 4. The obtained findings are presented in Sect. 5, with a final comprehensive evaluation and commentary in the last section.

2 Integration Studies

The task of assigning jobs to machines is informed by process planning, which determines the sequence of machines for each job. Scheduling problems can be studied in isolation or in integration with other factors such as process planning, due date assignment or delivery.

2.1 Integrated Process Planning and Scheduling (IPPS)

Regarding IPPS, Hutchison et al. [3] proposed two offline and one real-time scheduling plan. Although the plan gives the general optimum solution, it can only be applied to small problems. Jiang and Hsiao [4] proposed an analytical solution to the problem, but their 0–1 binary programming can only be applied to small problems. Zhang and Mallur [5] developed an integrated model consisting of three modules. These modules are process planning, production scheduling and decision-making module.

Brandimarte [6] used a multi-objective approach to utilize process plan flexibility in scheduling. Kim and Egbelu [7] studied the scheduling problem involving alternative process plans. Research has shown that mathematical models are useful in solving small problems, but they have not been as successful at solving larger problems. In most of the studies from the 90s, the problems were generally small and discrete, while in the early 2000s, larger problems and alternative routes were studied. Yang et al. [8] considered an IPPS problem that aims to minimize the total completion time for a single-machine parallel batching with disparate job families. Recent studies have used artificial intelligence and heuristic algorithms (and simulation in a few studies) to study more realistic integration problems where dynamic process plans, uncertainties and multiple objectives are realized rather than just achieving integration. In the literature, heuristic solutions are generally used for these problems. When the studies are analyzed, it is observed that batch manufacturing has been studied in a limited number of studies. The number of studies that attribute different importance to customers is extremely small.

2.2 Scheduling with Due Date Assignment (SWDDA)

Gordon et al. [9] conducted a comprehensive literature review in the field of SWDDA and noted that there is a continuous interest in SWDDA studies. The authors noted that in the context of Just in Time (JIT) production, the completion of jobs is expected to match the delivery date precisely rather than before the delivery date, as is typical in traditional production environments. This is since completing jobs too early or too late can result in additional costs associated with either late or early completion. According to Cheng et al. [10], earliness leads to unnecessary inventory holding and tardiness leads to customer dissatisfaction and contract non-compliance costs. Zhao et al. [11] investigated single-machine scheduling and due date assignment, where the processing time of a job depends on both its start time and its position in a queue. Xiong et al. [12] consider a single-machine SWDDA problem in an environment where a machine breaks down randomly at a given time with a certain probability.

The performance functions in SWDDA problems can be composed of factors such as earliness, tardiness, number of tardy jobs, due date-related costs and due window-related costs. In most of the studies in the literature, due dates are given in terms of process times and the number of operations, but customer weights are not considered. It is notable that the integration of single machine scheduling and common due date is widespread in most of the studies conducted in the 90s. Generally, the cost of earliness and tardiness has been considered, and due date-related costs are mentioned in very few studies. The number of studies that mention important customers is very limited.

2.3 Integrated Process Planning, Scheduling and Due Date Assignment (IPPSDDA)

Although the integration of the three functions has the potential to produce very efficient results, it has not yet found a large place in the literature, probably because it is a difficult and complex topic. There are only a few studies on the IPPSDDA problem. Demir and Taskin [13] studied this issue as a Ph.D. thesis. Then, Çeven and Demir [14] studied performance improvement by integrating the due date with the IPPS problem in their Master thesis. In the following years, studies such as Demir et al. [15–17] continue to cover the topic. Erden [18] dynamized the integration of three functions with stochastic and dynamic arrivals. Jobs can arrive at the SF at any time according to an exponential distribution. Demir and Erden [19] solved the dynamic IPPSDDA problem with an ant colony algorithm. Erden et al. [20], Demir et al. [21], Demir and Phanden [22], Demi̇r et al. [23] and Demi̇r et al. [24] solved the IPPSDDA problem using hybrid evolutionary strategy, tabu search and annealing simulation, particle swarm optimization.

2.4 Integrated Production and Delivery Scheduling (IPDS)

In studies where scheduling is integrated with delivery, the concept of delivery is sometimes expressed with different concepts such as vehicle routing, delivery, distribution, and transportation. These studies also try to optimize delivery in different ways. For example, in some studies, delivery is done by the manufacturer and the products are delivered to the customer's doorstep (Tonizza Pereira and Seido Nagano [25]; Garcia and Lozano [26]. In some studies, delivery optimization is performed until the moment when the products are loaded onto the vehicle and the vehicle's path is not examined [27]. In some studies, third-party logistics (3PL) companies are used for delivery planning [28]. Zografos and Androutsopoulos [29] proposed a method for routing and scheduling trucks carrying hazardous materials using heuristic algorithms. Chen et al. [30] presented a nonlinear mathematical model for scheduling the production of perishable food products and routing delivery vehicles. Fu et al. [31] developed a two-stage heuristic algorithm integrating scheduling and vehicle routing in a company in the metal packaging industry.

In the context of integrated production and delivery, previous studies have shown that scheduling and delivery functions are typically combined, while process planning, and due date assignment are often disregarded. Additionally, some studies have only focused on optimizing delivery up until the loading of products onto the vehicle, without considering the vehicle's route. Most of the integrated studies have concentrated on straightforward delivery operations, such as direct shipments to customers or predetermined/fixed routes, with an emphasis on minimizing transportation costs. However, no prior research has explored the importance of customers in the delivery phase. Moreover, unlike previous literature, this research will investigate how the distance traveled by the vehicle during the delivery phase influences performance.

3 Methods

This study employs a combination of ES and SA methods to achieve integration. ES is regarded as the forerunner of GA, differing from the latter in that it solely employs mutation operators, eschewing crossover operators altogether. The initial step of ES involves adding the chromosomes from the extant population, initially comprising ten chromosomes, into an array and subsequently calculating and recording their performance values, equivalent to the population size. The performance values are then ranked in ascending order, and the selection probabilities for each chromosome are computed accordingly. A mutation is then performed by randomly selecting a chromosome based on the selection probability. A total of 10 chromosomes are altered, and their mutated counterparts are retained in the mutation array. Performance values for the current and mutational populations are computed, and the chromosomes are sorted in ascending order based on their performance. The best chromosomes and population sizes are carried forward to the next iteration, and the process is repeated for several iterations.

Simulated annealing (SA) is a heuristic algorithm that circumvents the issue of being trapped in a local optimum by incorporating stochasticity, which allows it to explore solutions in a larger search space [32]. SA is a prevalent method for solving combinational NP-hard problems [33]. Initially, SA generates new solutions using a cooling rule from an initial temperature and evaluates them against an initial solution. If the new solution is better, SA transitions to the new solution [34]. However, to avoid becoming trapped in local optima, SA must occasionally accept new solutions that are inferior to the current solution. The selection of which suboptimal solutions to accept is determined stochastically using a probability function. The distinguishing characteristic of SA from other neighboring search algorithms is its ability to evade local minima. This ability is solely due to the algorithm's willingness to accept suboptimal solutions to a certain extent [35].

4 The IPPSDDAD Problem

In the study, a job shop-type manufacturing environment with one vehicle is discussed. In this environment, it is aimed that process planning, scheduling, due date assignment and delivery operations work in an integrated manner. When an order is received, the due date is determined by considering the customer, operation, and route information of this order, then this order is scheduled according to the machine densities, and after the production is completed, it is loaded on the vehicle and delivered to the customer.

4.1 Definition and Modeling of the Problem

The problem involves numerous customers and requires consideration of two distinct production routes for each job, with every job having three operations. The significance of each customer varies based on their level of importance categorized as very important, important, moderately important, or slightly important. Each classification is assigned a corresponding value: 2.5, 1, 0.5 and 0.33, respectively; higher values are given to more significant customers who take priority in scheduling and due date assignment when solving the problem using either individual delivery or batch-type delivery methods.

Integration into an SF must first be supported by process strategies. The process plan comprises information such as the jobs on the SF, their operations, the machines on which they will be performed, their times of operation, etc. Table 1 provides an illustration of a process plan.

Table 1. Sample Process Plan

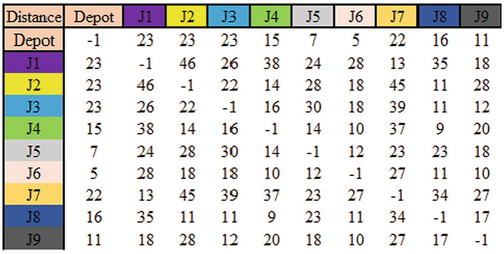
Jobs	Routes	Op. 1 (Machine)		Op. 2 (Machine)		Op. 3 (Machine)		Customer Importance
J1	R0	6	1	5	2	9	2	2.50
	R1	8	2	6	2	5	1	
J2	R0	9	2	8	1	3	1	0.50
	R1	8	1	4	1	3	2	
J3	R0	3	1	3	1	9	2	2.50
	R1	4	1	7	2	6	1	
J4	R0	9	2	5	2	7	1	1.00
	R1	6	2	7	1	5	1	

After determining the information about the jobs, the assignment of jobs to batches is performed. Each job belongs to only one batch and each batch has five jobs (customers). When allocating jobs to batches, the processing time in the SF (p_j), the importance of the customer (w_j) and the distance of the customer to the SF (d_{0j}) are calculated as in Eq. (1) below. After the batching values (BV) of the jobs are determined, the jobs are divided into batch groups of five by sorting the BV from smallest to largest.

$$BV = \left(\sum p_j + d_{0j}\right) * \frac{1}{w_j} \tag{1}$$

Having knowledge about the location of each customer is essential to ensure successful delivery. In this study, customer locations are defined as random points on a coordinate system. The SF is considered the center (0, 0) in the coordinate system. The distances to each other and to the SF are calculated using Eq. (2) where d_{ij} represents the distance and x and y represent the coordinates. Figure 1 shows the distance matrix by the determination of all distances.

$$d_{ij} = \left|(y_j - y_i)\right| + \left|(x_j - x_i)\right| \tag{2}$$



Distance	Depot	J1	J2	J3	J4	J5	J6	J7	J8	J9
Depot	-1	23	23	23	15	7	5	22	16	11
J1	23	-1	46	26	38	24	28	13	35	18
J2	23	46	-1	22	14	28	18	45	11	28
J3	23	26	22	-1	16	30	18	39	11	12
J4	15	38	14	16	-1	14	10	37	9	20
J5	7	24	28	30	14	-1	12	23	23	18
J6	5	28	18	18	10	12	-1	27	11	10
J7	22	13	45	39	37	23	27	-1	34	27
J8	16	35	11	11	9	23	11	34	-1	17
J9	11	18	28	12	20	18	10	27	17	-1

Fig. 1. Distance matrix

The chromosome comprises three important genes: due date assignment, scheduling, and delivery. The former consists of four rules while the latter two contain ten and nine rules respectively. Integration of these selected rules solves the problem at hand, with each set being formed through a combination of function values and route values to constitute a gene within the larger chromosome structure detailed in Fig. 2.

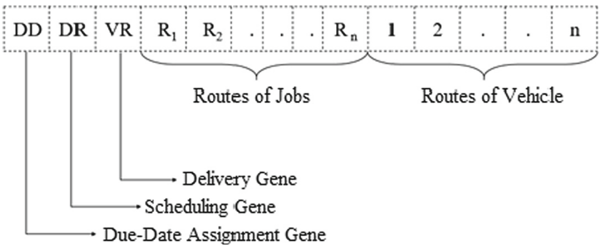


Fig. 2. Chromosome

For each rule, there is a gene value in the relevant gene. The values of the rules according to the functions are shown in Table 2.

Table 2. The Values of the Rules in the Gene

Gene Number	Due Date Assignment	Scheduling	Delivery
0	WSLK	WSPT	Single delivery
1	WPPW	WSOT	Batch delivery
2	WNOP	WLOT	Nearest neighbor
3	WTWK	WLPT	Savings algorithm
4		WATC	Sweep algorithm
5		ATC	Random delivery
6		MS	Hybrid delivery
7		WMS	Importance algorithm 1
8		EDD	Importance algorithm 2
9		WEDD	

4.2 Performance Criterion

The performance criterion is a function based on delivery time. This function penalizes the promised due date, tardiness, if any, and earliness, if any. The tardiness is calculated by Eq. (3) and earliness is calculated using Eq. (4).

$$T_j = \max(c_j - d_j, 0) \tag{3}$$

$$E_j = \max(d_j - c_j, 0) \tag{4}$$

The penalty values are determined using Eq. (5) and (6), where w_j is the customer's weight, c_j is the completion time and d_j is the delivery date, respectively.

$$P_E = w_j * (5 + 4 * (\frac{E}{480})) \tag{5}$$

$$P_T = w_j * (10 + 8 * (\frac{T}{480})) \tag{6}$$

In contrast to prevailing models in the literature, this study includes a promised due date because of its alignment with the just-in-time production philosophy's emphasis on timely job completion [9]. The philosophy prioritizes meeting deadlines precisely and considers early or late completion unfavorable. Thus, the performance function incorporates the promised due date, where higher values correspond to longer promises. However, given the problem nature at hand, lower performance function values are preferable. Therefore, assigning jobs closer to their time minimizes penalties calculated through Eq. (7) for non-adherence to due dates. The total penalty for a job (unit cp) is the sum of the P_D, P_E, P_T as formulated in Eq. (8). The performance criterion (PC) of the study is to minimize the sum of the penalties calculated for all jobs as shown in Eq. (9).

$$P_D = w_j * (8 * (\frac{D}{480})) \tag{7}$$

$$P_j = P_D + P_E + P_T \tag{8}$$

$$PC = \sum_{j=1}^{n} P_j \tag{9}$$

5 Results

For the problem, a software program is developed in Python programming language using PyCharm IDE on a computer with Intel(R) Core(TM) i7-4700HQ processor with 2.40 GHz and 16 GB RAM. NumPy, Matplotlib, random and math libraries are utilized.

First, ten different rule-free solutions are tried and averaged, and the results are recorded. Then, the results are obtained using the solution methods used in the study. For a more accurate evaluation and comparison, the iteration numbers are kept equal (100), and all random numbers used in the software are fixed. The results of SF 2 are shown in Table 3.

Table 3. The results of SF 2

Methods	ES	SA
SIRO-RDM	801806,4 cp	
Best (cp)	464487,2	504247,2
Improvement Rate	%42,07	%37,11

The results show that the highest rate of improvement is achieved with the ES. Each job represents a different customer. Each SF is solved by two different solution methods and the results of their performance are shown in Table 4.

Table 4. Results of the SF's

Methods	SF 1	SF 2	SF 3	SF 4
ES	**54222.7 cp**	**464487.2 cp**	**1144144.2 cp**	**1603461.2 cp**
SA	55937.4 cp	504247.2 cp	1203021.8 cp	1688062.2 cp

According to the results, the ES outperformed the SA in all four SF. In each SF, the performance of due date assignment, scheduling and delivery rules are analyzed for the chromosomes that performed best with ES. The analysis of the due date assignment rules is shown in Table 5.

The WSLK rule clearly outperforms other due date assignment rules. In all SFs, the WSLK rule had the best performance for the due date assignment. In SF 1, the

Table 5. The Analysis of the Due Date Assignment Rules

Rules	SF 1	SF 2	SF 3	SF 4
WSLK [0]	54222.7 cp	464487.2 cp	1144144.2 cp	1603461.2 cp
WPPW [1]	329531.4 cp	966147.6 cp	1391836.5 cp	1980590.6 cp
WNOP [2]	317710.2 cp	868822.8 cp	1309218.7 cp	1841577.8 cp
WTWK [3]	281890.2 cp	812662.8 cp	1269397.2 cp	1789976.5 cp

global performance of WSLK performed almost five times better than the other rules. Similar circumstances exist in other SFs. Nevertheless, it is important to note that the ratio declines as the number of employments grows. Table 6 displays the analysis of the scheduling rules.

Table 6. The Analysis of the Scheduling Rules

Rules	SF 1	SF 2	SF 3	SF 4
WSPT [0]	54222.7 cp	469933.2 cp	1143556.2 cp	1615156.6 cp
WSOT [1]	53575.5 cp	464487.2 cp	1147084.2 cp	1603461.2 cp
WLOT [2]	55403.5 cp	470309.2 cp	1147084.2 cp	1609669.2 cp
WLPT [3]	53575.5 cp	464487.2 cp	1147084.2 cp	1603461.2 cp
WATC [4]	54581.1 cp	464487.2 cp	1147084.2 cp	1603461.2 cp
ATC [5]	54581.1 cp	464487.2 cp	1147084.2 cp	**1603461.2 cp**
MS [6]	54222.7 cp	467365.8 cp	**1144144.2 cp**	1605789.2 cp
WMS [7]	54222.7 cp	467365.8 cp	1144144.2 cp	1605789.2 cp
EDD [8]	**54222.7 cp**	**464487.2 cp**	1147084.2 cp	1603461.2 cp
WEDD [9]	54222.7 cp	464487.2 cp	1147084.2 cp	1603461.2 cp

The scheduling rules don't show any clear dominance of one rule. The scheduling rules on the chromosome that produce the greatest results vary from SF to SF. The EDD (early due date) rule predominates in SF 1 and 2, the MS (minimum slack) rule in SF 3, and the ATC (apparent tardiness cost) rule in SF 4.

In SF 2, it is found that the scheduling rule WLOT for the chromosome with the best result leads to the greatest divergence from the best result. In this analysis, only the effect of the rule on a single chromosome is evaluated since the results obtained by changing only one gene (the scheduling gene) are analyzed. Therefore, at different iteration numbers and randomness, the results of the rules may differ. Changing a rule on the best chromosome can lead to a better result. However, it should be noted that a better solution is sometimes not achievable due to the small number of iterations, staying at the local optimum or the structure of the problem/rule. The results of the delivery rules for the best chromosome are shown in Table 7.

Table 7. The Analysis of the Delivery Rules

Rules	SF 1	SF 2	SF 3	SF 4
Single delivery [0]	98674.0 cp	930892.0 cp	2340006.0 cp	3511654.4 cp
Batch delivery [1]	64758.8 cp	632697.2 cp	1537654.4 cp	2428633.8 cp
Nearest neighbor [2]	**54222.7 cp**	490915.0 cp	1283879.0 cp	1724700.0 cp
Savings algorithm [3]	53864.2 cp	**464487.2 cp**	**1144144.2 cp**	**1603461.2 cp**
Sweep algorithm [4]	75726.7 cp	553585.2 cp	1335392.6 cp	1883753.2 cp
Random delivery [5]	75618.0 cp	617485.8 cp	1528558.4 cp	2233588.6 cp
Hybrid delivery [6]	55831.5 cp	524447.2 cp	1231944.6 cp	1827778.8 cp
Importance algorithm 1 [7]	58499.3 cp	522287.2 cp	1348608.6 cp	1789018.8 cp
Importance algorithm 2 [8]	58499.3 cp	525119.2 cp	1366528.6 cp	1812458.8 cp

In the analysis of the delivery rules, the savings algorithm is in the chromosomes that performed best in three of the four shop floors. The savings algorithm is, in fact, the top-performing rule in each of the SFs, but due to SF 1's constrained solution space, it wasn't in the best chromosome. However, the single delivery rule without batches performed 45% worse than the savings algorithm in SF 1 by 45%, SF 2 by 50%, SF 3 by 51%, and SF 4 by 54%. These percentages show that delivering in batches results in a more effective overall solution to the problem. It is obvious that single delivery [0], batch delivery [1], and random delivery [5] rules typically achieve the worst performances.

The findings indicate that altering the delivery rule on a given chromosome can have a notable impact on its performance, more so than modifying scheduling rules. Therefore, it can be concluded that delivery rules are more effective in changing the global solution than scheduling rules. On SF 1, the saving algorithm outperformed the closest alternative rule by 0.7%, while on SF 2, 3, and 4, the difference is even greater, at 5.4%, 7.1%, and 7.0%, respectively.

6 Discussions

This study aims to integrate the four basic manufacturing functions, namely process planning, scheduling, due date assignment, and delivery, for the first time in the literature. Moreover, customer priority levels are considered throughout the due date assignment, scheduling, and delivery stages, which is not commonly addressed in prior studies. However, in accordance with the Just-In-Time (JIT) philosophy, the objective function heavily weights the concepts of earliness, tardiness, and due date.

The problem involves four different shop floors, each containing 25, 50, 75, and 100 jobs respectively, belonging to different customers. Each shop floor has two machines and two different routes are considered for scheduling each job. The complexity and size of the problem necessitate the use of ES and SA algorithms to obtain a solution, where each solution is represented by a single chromosome. The performance of the shop floor, the two algorithms used for the solution, and each manufacturing function under different rules have been thoroughly evaluated.

The results indicate that the heuristic algorithms employed perform 42% better than SIRO-RDM, underscoring the importance of integration. ES outperforms SA in all shop floors among the solution methods. In the due date assignment rules, WSLK exhibits superior results on all shop floors. In scheduling rules, EDD (early due date) rule on the first and second shop floors, MS (minimum slack) rule on the third shop floor, and ATC (apparent tardiness cost) rule on the fourth shop floor stand out. Delivery-focused rules such as EDD and MS show more effective performance in scheduling. The savings algorithm performs better than other rules in delivery rules.

The study concludes that the due date assignment rules have a more prominent effect on the global performance of the functions than the scheduling and delivery rules. Thus, determining a good due date is crucial, and it is more effective for the company to determine the due date internally rather than from outside the factory without considering the conditions.

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