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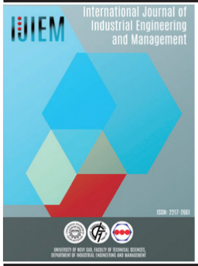

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Comparing sequential and integrated models in Reconfigurable Manufacturing Systems optimization

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ABSTRACT

Consumers are increasingly seeking products with a higher degree of customization, and this has intensified the search for more flexible production systems. Unexpected phenomena, including those impacting the economy and public health, have shown the need for high reactivity by manufacturers. Reconfigurable Manufacturing Systems are one of the means to respond to new market needs. They are designed to be able to quickly change their structure and thus adapt their functionalities and capabilities. A central question with regard to these types of systems is when and how they should be reconfigured. It is, however, a question that needs to be addressed simultaneously alongside the classic resource allocation and scheduling problems, since the problems are interdependent. This paper proposes four models that address the problem sequentially, partially sequentially, and integrally. Our numerical analysis demonstrates the advantage and importance of treating these problems in an integrated manner. In addition, we provide and compare three exact methods for the integrated process planning, layout, and scheduling optimization problems. The exact methods are integer linear programming, constraint programming, and constraint programming with search strategies, which our numerical examples show to be greatly superior to the two others. Finally, we present a problem at an industrial scale.

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1. Introduction

To remain competitive, companies need to adapt to changes in markets and to changing demand. With accelerating globalization, consumers increasingly make choices based not only on quality and price, but also on variety and product customization. In addition, some recent events have created additional instability and unpredictability in markets; these include the Covid-19 pandemic, as well as ongoing wars and economic crises. Changes like these highlight the need for resilient and reactive production systems such as Reconfigurable Manufacturing Systems (RMS). RMS can respond quickly to abrupt changes by reconfiguring hardware and software at the system, machine, and control levels [1]. At the system level, they are able to change the positioning of machines and equipment in the layout, which directly affects the handling of materials, accounting for 20% to 50% of the total production system costs [2].

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Most studies in this field concern RMS optimization. Optimization seeks to make manufacturing more efficient. The motivation behind the best-known optimization problems is reducing production times and costs. They can, however, also be applied with other aims in view, such as reducing environmental impacts, increasing machine reliability, and many others.

The work presented in this paper optimizes three distinct problems: Process Planning, Layout Design, and Scheduling. While these problems are often analyzed separately, they share common variables that mutually influence each other. Integrating these problems may therefore yield better results as regards the total production cost. Integrating problems of process planning and scheduling has already been done for non-RMS problems [3], [4], but integrating them in the context of RMS presents new challenges due to system reconfigurability. Moreover, one feature of RMS is the possibility of reconfiguring the layout by moving machines around, and it therefore becomes essential to integrate layout alongside process planning and scheduling, since there are common variables used by all three problems in the allocation of resources. Production and machine reconfiguration costs and times directly impact the sequencing of operations in process planning and scheduling. For layout and scheduling, what impacts most are the layout reconfiguration and material handling times. For process planning and layout, we focus on the material handling costs and the layout used. Moreover, the tardiness penalty affects all the problems.

Four models are proposed to completely solve process planning, scheduling, and layout. The first treats each problem individually and sequentially. The second and third each integrate two problems, the remaining problem being handled sequentially. The fourth model integrates the three problems directly. All models have as their final objective to minimize total production costs, including costs of manufacturing, machine reconfiguration, layout reconfiguration, material handling, and tardiness.

This paper is organized as follows. Section 2 reviews the literature on process planning, scheduling, and layout design problems (individually and jointly) in the RMS context. Section 3 describes the proposed problem. Section 4 presents the model formulations. Section 5 explains the exact methods. Section 6 illustrates some small numerical example instances and compares them. Section 7 presents an industrial-scale example. Finally, Section 8 contains our conclusions and mentions future prospects.

2. Literature review

Our paper specifically contributes to the optimization of configurations, addressing the problems of process planning, layout design, and scheduling. While these three optimization problems have been extensively studied individually or in pairs, few works have explored the optimization of all three aspects simultaneously. This section presents a literature review on the three optimization problems individually and jointly, identifies research gaps, and compares our paper to existing studies.

2.1 Process planning for RMS

Process planning (PP) involves determining the components and operations required for manufacturing a product [5]. In the context of RMS, where the system is reconfigurable, process planning aims to select the job execution order of operations and the machines/configurations to which the operations are assigned.

Metaheuristics are commonly employed to address RMS optimization problems, given the limitations of exact methods when dealing with real-size instances [6]. In a study by Musharavati [7], four different Simulated Annealing (SA) approaches were investigated. The authors sought to minimize costs, the costs in question being the costs of changing processes, changing set-ups, changing tools, and changing configurations, as well as overall operating costs.

Some researchers extend their objective functions beyond cost considerations, incorporating time-related functions. Xiaowen [8] examined a multi-stage production line, using a model based on graph theory, with the line configuration and the optimal manufacturing path being determined each time there was a product production changeover. The focus was on minimizing both reconfiguration time and costs.

Another dimension of objectives under study involves environmental considerations. In Khezri [9], a process plan was generated for a single product, addressing a multi-objective problem. Alongside objectives commonly found in the literature (cost and functions related to time), a sustainability-metric function was included to take account of hazardous liquid waste and greenhouse gases emitted during processing. Khettabi [10] addressed a very similar objective function for the final process plan selection. In contrast to the aforementioned works, Massimi [11] concentrated on a single objective, namely minimizing energy consumption with reference to two RMS characteristics, integrability and modularity, the aim being to identify the sequence of operations for a single product unit, as well as the machines and modules for processing each operation.

Approaching the question from a different perspective, Khan [12] focused on a part on a single machine. The objective was to reduce lead time by minimizing the time required for tool changes and setup. Gonnermann [13], in the context of a process planning and process monitoring problem for assembly lines, devised a comprehensive methodology comprising four modules: the first module generates assembly plans, the second handles the monitoring process, the third optimizes the two preceding modules, and the final module performs a simulation to verify collision freedom and feasibility in process planning. The objectives here were minimizing reconfiguration costs and cycle time while maximizing the level of monitoring efficiency.

2.2 Layout configuration for RMS

A distinctive feature of RMS is the ability to change the physical positioning of equipment, which has a direct impact on the time and cost of material handling (MH) and system reconfiguration. In a study by Guan [2], the layout design problem was modeled as a quadratic assignment problem that involved minimizing the cost of transporting loaded and unloaded Automated Guided Vehicles between workstations. In a more recent work, Wei [14] considered a problem involving different sized rectangular-shaped pieces of equipment able to move on a continuous shop floor. The objective was to minimize material handling and layout reconfiguration costs while maximizing the area of workshop in use.

In contrast, Han [15] introduced a layout feasibility tool incorporating different configuration parameters relating to storage, transport path, processing, preparation, and tool handling. The values of the various parameters are entered by users, and the program assesses whether or not the combination of values is valid. Arnarson [16] concentrated on minimizing the total cost of material handling (MH) by robot platforms.

2.3 Scheduling for RMS

The scheduling problem in RMS involves determining the start and completion times of operations, taking account of resource utilization constraints. Mokhtari [17] investigated ways of improving the makespan in a flow shop through the use of a group search optimizer algorithm. Ruiz-Torres [18] sought to minimize the tardiness of a two-stage hybrid flow shop, in a study that involved determining the number of workstations used in each period (shifts), assigning workers, and scheduling their jobs.

For handling real-time job arrivals, Yang [19] proposed a system architecture comprising a reconfiguration agent and a scheduling agent. The reconfiguration agent analyzes the current system configuration and determines whether reconfiguration is required, while the scheduling agent indicates which jobs should be performed. Both agents utilize priority dispatching rules to inform their decisions.

Focusing on time-related functions, Deif [20] addressed a capacity scalability scheduling problem to improve the ordinary scalability of flexible manufacturing systems. Ordinary scalability typically involves a fixed capacity that is determined at the start of planning. The authors developed a computer tool for determining when and by how much to re-scale.

2.4 Integrated process planning and scheduling for RMS

The three optimization problems, when treated individually, will often yield good results specific to the problem at hand. However, an integrated approach to solving these problems, considering the production process as a whole, might be expected to provide superior results due to the numerous intersection points between them. In essence, process planning aims to identify the optimal machines and configurations for manufacturing a particular product. Scheduling, on the other hand, specifies when each operation should be executed within a defined time horizon and with respect to a given set of products. The best machine/configuration for an individual product may not necessarily be the optimal choice when evaluating the whole production process over a given period.

Yu [21] developed a model for determining the sequence of the various elements within the system, for designating the operation/machine to be used for each element, and for assigning sequences to machines based on the process route and fixture availability. The model leverages a multi-objective heuristic based on priority rules in order to minimize makespan, mean flow time, and mean tardiness. The objective function was subsequently extended by Ivanov [22] including the minimization of production costs. The authors introduced a control approach *"with dynamic structural-logical con-*

straints". Their reason for using this terminology was that dynamically changing operation sequences may impose dynamic and nonlinear requirements in the constraints for controlling machines and operations. Dou [23] addressed a multi-part optimization problem within the same family, with the objective of minimizing total cost, where total cost encompasses capital and reconfiguration costs and tardiness. The model determines the number of stations and parallel machines, the machine types, the assignment of operations to machines, and the final scheduling.

2.5 Integrated process planning and layout configuration for RMS

In addition to production costs, material handling (MH) contributes significantly to total system cost, ranging from 20% to 50% [2]. When seeking to reduce overall cost, it is essential to consider MH. Altering the physical arrangement of equipment can optimize MH costs, but this will incur additional costs relating to layout reconfiguration. It is, however, possible to achieve a balance between reducing MH costs and limiting reconfiguration expenses as a result of the flexibility offered by RMS, such as the ability to select machines for operations — a choice that is closely tied to final process planning. Integrating layout reconfiguration and process planning can improve overall performance.

Campos Sabioni [24], [25] proposed two papers integrating process planning and layout reconfiguration with product configuration, focusing on modular products. In this approach, customers do not choose specific product modules but express their requirements, which are translated into a product optimized for production. In both papers the aim is to minimize total cost, which encompasses costs of raw material, production, machine reconfiguration, layout reconfiguration, and material handling.

2.6 Integrated layout configuration and scheduling for RMS

As we highlighted in the previous subsection, integrating layout and scheduling problems is important, particularly as regards optimizing MH. The scheduling of operations in the time horizon means finding a balance between MH, layout reconfiguration costs, and times. This balance significantly impacts factors like tardiness and makespan.

Guo [26] addressed an assembly problem involving fixed-position assembly islands, where products cannot be moved during production, for reasons relating to such factors as size and fragility. To manage the organization of resources and times, the authors proposed a synchronization-oriented reconfiguration mechanism based on the industrial internet of things and digital twins. The primary objective was to minimize waiting and set-up times, with additional analysis relating to set-up amounts and tardiness.

In Yang [27], concerning real-time optimization of production systems, the goal was to minimize total tardiness. The model proposed not only optimizes scheduling but also considers reconfiguration decisions, where each "mode" corresponds to a specific workshop layout and configuration of production resources. In Ghanei [1], sustainability parameters were taken into account and a model proposed with the objective of minimizing the accumulated costs of energy consumption, layout reconfiguration, and material handling. Ye [28] focused on multi-part modular products in a reconfigurable Cellular Manufacturing System, with a view to minimizing total cost, including production costs, layout reconfiguration (intracellular and extracellular), machine idle time, material handling, and work in process (WIP) inventory.

In the context of line balancing, the aim in Khan [29] was minimizing total time while maximizing the line efficiency index and customer satisfaction index. The authors developed a heuristic with four variants, considering reconfiguration possibilities at both the machine and layout levels.

2.7 Integrated process planning, layout configuration, and scheduling for RMS

Integrating process planning, scheduling, and layout problems in RMS can potentially yield better global results through the use of shared variables. However, it is important to note that the when these problems are integrated, the computational cost of solving them will increase, given that each of them individually is already NP-hard [2], [9], [17].

To the authors' best knowledge, very few papers have attempted to integrate these three problems. In a previous work [30], we proposed a model for minimizing total cost and validated it using an exact method. Another study by Gao [31] focused on cost minimization while also considering the minimization of tardiness, hazardous waste, and greenhouse gas emissions.

Table 1. Summary of the articles cited in the literature review

Paper	Solving Methods	Objective Function	PP	L	S	Year
[28]	Exact and GA	Total cost	-	x	x	2006
[20]	GA	Physical capacity and reconfiguration costs	-	-	x	2007
[7]	Simulated annealing	Total cost	x	-	-	2012
[15]	Layouts' feasibility tool and flow control propositions	Feasibility tool, does not have an objective function	-	x	-	2012
[2]	Exact, revised electromagnetism-like mechanism and GA	Total material handling cost	-	x	-	2012
[8]	GA	Reconfiguration costs and times	x	-	-	2013
[21]	Heuristics using Priority scheduling approaches	Makespan, mean flow time, and mean tardiness	x	-	x	2013
[23]	Exact and NSGA-II	Total cost and total tardiness	x	-	x	2015
[17]	Group search optimizer algorithm	Minimize the makespan	-	-	x	2015
[14]	Chaotic generic algorithm, GA, NSGA-II, and ant colony algorithm	MH and layout reconfiguration costs, utilization of workshop area	-	x	-	2019
[9]	Exact, strength pareto evolutionary algorithm II and NSGA-II	Sustainability-metric, total production time and cost	x	-	-	2020
[11]	A heuristic-based non-linear mixed integer approach	Energy consumption	x	-	-	2020
[22]	Dynamic control algorithm	Production costs and makespan	x	-	x	2020
[1]	Exact and GA	Energy consumption, layout reconfiguration and MH costs	-	x	x	2020
[12]	GA and cuckoo search	Tool and set-up changes	x	-	-	2021
[10]	NSGA-II, NSGA-III, weighted GA and random weighted GA	Total production time and cost, hazardous liquid waste and GHG emission	x	-	-	2021
[26]	Synchronization-oriented reconfiguration mechanism	Total waiting and set-up times	-	x	x	2021
[25]	GA	Total cost	x	x	-	2021
[24]	Hybrid approach: modified brute-force algorithm + GA	Total cost	x	x	-	2021
[27]	Deep reinforcement learning, iterated greedy and GA	Total tardiness	-	x	x	2021
[18]	Heuristics	Average tardiness	-	-	x	2021
[31]	Exact and NSGA-III	Sustainability-metric, tardiness and costs	x	x	x	2021
[30]	Exact	Total cost	x	x	x	2022
[29]	Heuristic	Total time, efficiency, and customer satisfaction	-	x	x	2022
[13]	Mixed-Integer Linear Programming	Reconfiguration costs, cycle time, and level of monitoring efficiency	x	-	-	2022
[19]	Deep reinforcement learning	Makespan	-	-	x	2023
[16]	NSGA-II	Total material handling of robot platforms	-	x	-	2023
This work	ILP, CP and CPS	Total cost	x	x	x	2023

2.8 Literature gaps

Table 1 summarizes the most relevant information (solving methods and objective functions) of the articles mentioned in this section. After reviewing the literature, we remark that most studies have focused on the problems individually, although integrating problems two-by-two has seen an increase in popularity. Since problems have decision variables in common, solving them jointly can in some cases improve overall results.

The main research gaps can be listed as follows:

- the vast majority of works focus on solving one of the problems individually, or on integrating two of them only;
- few works include an analysis of material handling costs and times in the layout problem;

- the possibility of reconfiguring the layout is one of the characteristics that set RMS apart, but layout optimization problems have received less attention than scheduling and process planning problems;
- exact methods are almost always used for model validation only, but an in-depth study of exact methods may potentially yield interesting results to be applied in conjunction with other methods;
- the papers that integrate the three problems have not yet shown their effectiveness in solving industrial-size instances; in our previous work [30] and Gao's [31] work, only small instances were tested;
- no relevant works have so far featured a numerical comparison of sequential, partial sequential, and integrated models.

With a view to filling some of these gaps, the contributions of the present paper are the following. Process planning, layout design, and scheduling problems are solved simultaneously. To the best of our knowledge, this is the first work that analyzes and compares sequential, partial sequential, and integrated models for solving these three problems. Different exact methods are developed to solve the problems jointly. Material handling times and costs are included in the layout problem. Finally, one industrial-scale example is proposed.

3. Problem description

This section describes the studied problem. Table 2 lists all the parameters and decision variables used in this work. Customer orders are considered as jobs $J_i \in \{J_1,\ldots,J_n\}$, translating required products into production orders. Each job J_i has a due date d_i before which the job is expected to be fully processed. Where a job is not completed before its due date, a job penalty cost W_i is incurred per time unit of tardiness. A job J_i is composed of n_i operations $J_i=\{O_{i1},\ldots,O_{i,n_i}\}$. They are specific manufacturing processes, and the set of operations necessary for a job must respect a known partial order of precedence. The precedence relation between operations of J_i is represented as $O_{ij} \lhd_i O_{ij'}$ where operation O_{ij} precedes \$O_{ij'}\$.

The manufacturing system has m machines M_k $(k=1,\ldots,m)$ to process operations. A machine may be fixed or mobile. Each machine M_k has q_k possible configurations $M_k\,[e](e=1,\ldots,q_k)$. A machine configuration is the combination of software and hardware modules. The time required $P_k^{\chi}(e,e')$ and the cost $K_k^{\chi}(e,e')$ of reconfiguring a machine depend on the machine M_k in question and on the initial and final configurations. When a machine reconfiguration is necessary, the machine remains unavailable while reconfiguration is occurring. The same reasoning applies to costs.

Each operation O_{ij} has at least one machine/configuration combination $M_k\,[e]$ capable of performing it. Each operation O_{ij} has an associated processing time $P_{ij}\,(k,e)$ and a cost $K_{ij}\,(k,e)$ if that operation is processed by machine k in configuration e. We have $P_{ij}\,(k,e)=\infty$ when a machine k in configuration e cannot perform an operation O_{ij}. Otherwise, $P_{ij}\,(k,e)$ is the number of time units needed for performing it. The same applies to cost, each combination having an associated cost, and where an operation cannot be performed by a given combination the cost is represented as infinite. By penalizing infeasible combinations with infinite costs, the optimization algorithm is guided toward feasible solutions that comply with the constraints. This helps ensure that the solutions generated by the algorithm are feasible and capable of being implemented in real-world scenarios. Assigning infinite costs to infeasible combinations can help improve the efficiency and effectiveness of the optimization algorithm by reducing the search space.

Regarding physical machine location, the problem considers a set of l possible layouts $\Lambda=\{\Lambda_1,\ldots,\Lambda_l\}$. Mobile machines will be moved when an optimized system is detected in another layout. A layout reconfiguration from configuration u to configuration u' has a cost $K^{\lambda}\,(u,u')$ and an execution time $P^{\lambda}\,(u,u')$. The associated cost comprises several elements and will depend on the means by which the machines are moved. For example, if they are moved using Automated Guided Vehicles (AGVs), the cost might include the energy consumed by the vehicles and costs of maintenance and depreciation. The execution time for a reconfiguration corresponds to the time needed for moving the various machines and positioning them in the new layout. There can be no changes within the same layout, so $\forall, P^{\lambda}(u,u)=0$. The other values are equal to the reconfiguration time. The same applies to layout reconfiguration costs.

Each layout configuration \$$u$\$ has corresponding material handling times $P_u^{\tau}(k,k')$ and costs $P_u^{\tau}(k,k') \times K^{\tau}$ of transferring operations from machine k to machine k'. The leading diagonal equals zero for all layouts because there is no travel time between a machine and itself. The other times are greater than zero. We multiply the MH times by K^{τ}, a material handling cost parameter (constant), to obtain the MH cost.

Table 2. Parameters and decision variables

Parameters	Description
$J=\{J_1,\ldots,J_n\}$	the set of jobs
$O_i=\{O_{i1},\ldots,O_{i,n_i}\}$	the set of operations of J_i
$M=\{M_1,\ldots,M_m\}$	the set of machines
$M_k=\{M_k[1],\ldots,M_k[q_k]\}$	the set of configurations of machine M_k
$\Lambda=\{\Lambda_1,\ldots,\Lambda_l\}$	the set of layouts
d_i	due date of job i
π_p	job with the due date in p^{th} position among the due dates in ascending order
W_i	penalty cost per unit of tardiness for J_i
T	time horizon, jobs being scheduled from 0 to T
$\lhd_i$	precedence relation over the set of operations of J_i, $O_{ij} \lhd_i O_{ij}$ has to be processed before $O_{ij'}$
$P_{ij}(k,e)$	O_{ij} processing time on machine M_k in configuration e
$P_k^{\chi}(e,e')$	machine reconfiguration time required for machine M_k to change from configuration e to e'
$P^{\lambda}(u,u')$	layout reconfiguration time to change from layout u to u'
$P_u^{\tau}(k,k')$	material handling time associated with a layout u when an operation of J_i is processed on machine k and its next operation on machine k'
$K_{ij}(k,e)$	O_{ij} production cost of performing O_{ij} with machine M_k in configuration e
$K_k^{\chi}(e,e')$	machine reconfiguration cost for machine M_k to change from configuration e to e'
$K^{\lambda}(u,u')$	layout reconfiguration cost to change from layout u to u'
K^{τ}	material handling cost per unit of time for moving J_i from one machine to another
Decision variables	**Description**
$S_{ij} \in \{0,\ldots,T\}$	start time of O_{ij}
$C_{ij} \in \{0,\ldots,T\}$	completion time of O_{ij}
$S_i = S_{i1}, C_i = C_{in_i}$	start and completion time of J_i
$\sigma_{ij} \in \{1,\ldots,n_i\}$	position of operation j in the processing sequence among all operations of J_i
$\sigma_i[p] \in \{1,\ldots,n_i\}$	operation executed in p^{th} position among all operations of J_i
$\mu_{ij} \in \{1,\ldots,m\}$	machine processing O_{ij}
$\lambda(t) \in \{1,\ldots,l\}$	layout used at time t
$\chi(k,t) \in \{1,\ldots,q_k\}$	configuration of machine k at time t

4. Model formulation

This section presents different mathematical models for optimizing process planning, layout design, and scheduling, and Table 2 lists all parameters used. All of these models seek to solve the three problems either sequentially or jointly. In all cases, the expected outputs are the start times S_{ij} and completion times C_{ij} of operations. Consequently, we have the start time S_i and the completion time C_i for each job J_i, the execution position σ_{ij} of its operations, the machine μ_{ij} processing each operation, the layout $\lambda(t)$, and the configuration $\chi(k,t)$ of each machine k used at each time t.

The problem is subject to the following assumptions: the demand is known; the due dates of the products are known; raw materials, workforce, and material handling (transport of products between machines) are always available; the performance of all jobs meets the required level of quality.

4.1 Different ways of modeling

There are different ways to model our problem. The first is to handle each of the three problems individually and sequentially. Another way would be to handle one of the three problems individually and sequentially while integrating the two others. The final option is to integrate the three problems.

For the model that treats the problems individually and sequentially, the sequence in which they are solved is crucial. The scheduling problem (S) should be the last one to be solved, since it gives the final information about when each action should be taken (production operation, reconfiguration, and material handling). As for the other two problems, whether process planning (PP) is solved before layout design (L), or vice versa, will depend on the modeling.

The three problems influence each other independently of the sequence, and some assumptions must be applied initially. If we start with the layout problem L, it is difficult to make decisions, since we lack certain relevant information, such as which machine a given operation is going to be assigned to. Without knowing the machines to be used and the sequence of operations, it is not feasible to identify a cost compromise between reconfiguring the layout and material handling, because the requisite information is lacking. In a scenario with good historical production data it might conceivably be interesting to start with L, but since we do not possess such data, in our modeling we start with process planning PP so that at least we have machine assignments as input to L. Although the layout has not yet been defined when PP is solved, we nevertheless need to use some hypothetical layout as input: this can be the initial layout, or, for example, a layout based on the weighted average of distances across all possible layouts.

After deciding the sequence in which the problems will be solved, some modeling possibilities remain, as listed in Table 3.

4.2 Sequential model: PP → L → S

The sequential model is divided into three steps, as presented in Figure 1: process planning, layout, and scheduling. The first step, process planning, analyzes each job individually and defines the machines and configurations that will perform each operation. This information is used as input for two subsequent steps. From this point onwards, jobs are evaluated together. The second step, layout, decides the layout used to process each job, together with the execution sequence of operations. Finally, the outputs from the two previous steps are used as input to the third step, where the final scheduling of operations is decided.

The problems are treated separately and sequentially. However, none of the problems can be handled completely in isolation, since there are variables in common that impact each other. For this reason, the initial data will sometimes be adapted to make it possible to divide up the subproblems.

Step 1: Process Planning (PP)

The process planning phase involves the allocation of operations to machines and configurations and must be done individually for each job. The objective function to minimize costs includes costs relating to production, material handling (MH), and tardiness ($f_{c_{pp}} = \sum \left(f_{p_{pp}} + f_{MH_{pp}} + f_{t_{pp}} \right)$). Production times and costs are the same as those in the overall problem input. For the MH data, some changes have been made. As no layout decisions are made in this step, the MH time between two machines is considered to be the average time for all MH layouts ($\overline{\Lambda}$). Due dates also change. The new value used for the due date will be the smaller value among on the one hand the original due date, and on the other hand the sum average of a job's worst and best production times.

$f_{p_{pp}}$ represents the total production cost for all the operations of job J_i in the process planning phase. The production cost ($K_{ij}(k,e)$) depends on the machine k and the configuration e that will perform the opera-

Table 3. Methods applied in this work

Methods	Description
PP → L → S	Each problem is handled individually and sequentially.
PP → L + S	The process planning problem is handled individually, while the layout and scheduling problems are handled together.
PP + L → S	The process planning and layout problems are handled together, and then the scheduling problem is handled individually.
PP + L + S	The three problems are handled together.

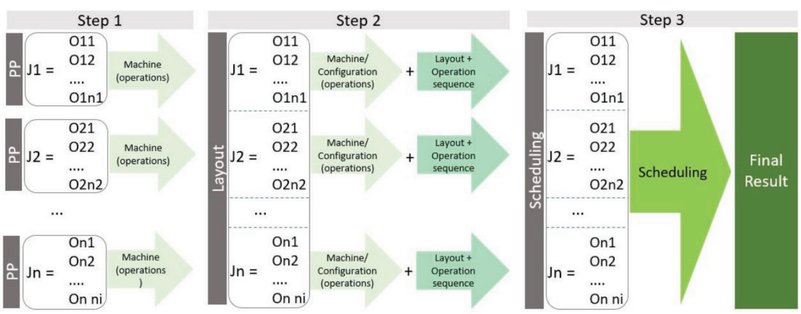

Figure 1. Sequential model

tions. We therefore need to define the decision variables μ_{ij} (machine responsible for performing O_{ij}) and $\chi(k,t)$ (configuration of machine μ_{ij} at time S_{ij}) (1).

$$f_{p_{pp}} = \sum_{j=1}^{n_i} K_{ij}\left(\mu_{ij}, \chi_{ij}\left(\mu_{ij}, S_{ij}\right)\right) \quad (1)$$

$f_{MH_{pp}}$ represents the total material handling cost for all the operations of job J_i in the process planning phase. The material handling cost corresponds to the constant parameter K^{τ} multiplied by the MH time ($P_u^{\tau}(k, k')$) between operations. For the MH time it is necessary to know the layout ($\lambda(t)$) used by operations (in this step all jobs have the same layout ($\overline{\Lambda}$)), the machines performing operations, and the operation sequence ($\mu_{i\sigma_i[p]} \rightarrow \mu_{i\sigma_i[p+1]}$) (2).

$$f_{MH_{pp}} = \sum_{p=1}^{n_i-1} K^{\tau} \cdot P_{\overline{\Lambda}}^{\tau}\left(\mu_{i\sigma_i[p]}, \mu_{i\sigma_i[p+1]}\right) \quad (2)$$

$f_{t_{pp}}$ represents the tardiness cost of job J_i in the process planning phase. This cost depends on job completion time and job due date (calculated as described above). If C_i is greater than d_i, this difference is multiplied by a penalty cost per unit of tardiness. Otherwise, it is zero (3). In our optimization model, the penalty cost per unit of tardiness is a crucial element for providing a measure of the impact of delays. This penalty cost can represent storage costs, lost revenue, decreased customer satisfaction, extra resource use, or contractual penalties. The way the penalty is calculated will vary according to the company and the product.

$$f_{t_{pp}} = W_i \cdot max(0, C_i - d_i) \quad (3)$$

There exist some constraints that allow the problem to be restricted. First, operations are non-preemptive. Therefore, if the start time (S_{ij}), machine (μ_{ij}), and configuration ($\chi(k,t)$) have already been chosen, it is possible to know the operation completion time (C_{ij}) by *adding the production time of the operation to the start time* (4).

$$C_{ij} = S_{ij} + P_{ij}\left(\mu_{ij}, \chi\left(\mu_{ij}, S_{ij}\right)\right) \quad (4)$$

The production order of operations must respect the job precedence order. In cases where operation O_{ij} precedes an operation $O_{ij'}$($O_{ij} \lhd_i O_{ij'}$), the position of O_{ij} is lower than the position of $O_{ij'}$ ($\sigma_{ij} < \sigma_{ij'}$) (5).

$$O_{ij} \lhd_i O_{ij'} \Rightarrow \sigma_{ij} < \sigma_{ij'} \quad (5)$$

An operation can start ($S_{ij'}$) only after the previous operation in the partial order $\lhd_i$ has ended (C_{ij}), and the material handling time ($P_u^{\tau}(k, k')$) between the machines performing the operations (μ_{ij} and $\mu_{ij'}$) is respected (6).

$$\sigma_{ij} + 1 = \sigma_{ij'} \Rightarrow C_{ij} + P_{\overline{\Lambda}}^{\tau}\left(\mu_{ij}, \mu_{ij'}\right) \leq S_{ij'} \quad (6)$$

Constraints 7 guarantee the link between operations and their execution sequence position.

$$\sigma_{ij} = p \Leftrightarrow \sigma_i[p] = j \quad (7)$$

Step 2: Layout (L)

This step aims to find the best layout for each job and the execution sequence of its operations. The allocation of operations to machines (that is to say, the output of PP) is used as input for this step. The objective function is to minimize costs. It includes layout reconfiguration, material handling, and delay costs ($f_{c_l} = \sum\left(f_{l_l} + f_{MH_l} + f_{d_l}\right)$. Here, production times are already known, because the machines and configurations used are also known. The only data that is not the same as in the original problem is the due date, which is considered to be zero for all jobs, meaning that jobs are completed as quickly as possible.

f_{l_l} represents the sum of layout reconfiguration costs during the production period of all the ordered jobs. Layout reconfiguration costs ($K^{\lambda}(u,u')$ depend on the layout sequence and the reconfigurations between them. The sequence is given by the jobs' due dates at this step (π_p). Note that $\lambda(0)$ is always the initial system layout (8).

$$f_{l_l} = \sum_{p=0}^{n-1} K^{\lambda}\left(\lambda\left(\pi_p\right), \lambda\left(\pi_{p+1}\right)\right) \quad (8)$$

f_{MH_l} represents the sum of material handling cost of all operations for all jobs in the layout phase. Material handling costs are similar to the function given in PP. The only difference is that the layout is not a constant ($\overline{\Lambda}$) parameter here, but depends on the job i ($\lambda(i)$) (9).

$$f_{MH_l} = \sum_{i=1}^{n} \sum_{p=1}^{n_i-1} K^{\tau} \cdot P_{\lambda(i)}^{\tau}\left(\mu_{i\sigma_i[p]}, \mu_{i\sigma_i[p+1]}\right) \quad (9)$$

f_{d_l} represents the sum of delay costs in the layout phase. Unlike tardiness costs, delay costs are not linked to completion time and due date. The sum of the layout reconfiguration ($P^{\lambda}(u,u')$) and material handling ($P_u^{\tau}(k, k')$) times is directly multiplied by a penalty cost (W_i) (10).

$$f_{d_l} = W_i \cdot \left[\sum_{p=0}^{p-1} P^{\lambda}\left(\lambda\left(\pi_p\right), \lambda\left(\pi_p + 1\right)\right) + \right.$$
$$\left. + \sum_{i=1}^{n} \sum_{p=1}^{n_i-1} P_{\lambda(i)}^{\tau}\left(\mu_{i\sigma_i[p]}, \mu_{i\sigma_i[p+1]}\right)\right] \quad (10)$$

There are only two constraints, which have already been used for PP. They are expressed in Equation 5, which indicates that precedence order must be respected, and Equation 7, which ensures that the model is consistent.

Step 3: Scheduling (S)

After going through the previous steps, the only remaining missing elements are the times when each operation will start and finish, such that machine and layout reconfiguration times and production capacities are respected. All the previous outputs are used as input for this step. The objective is to minimize machine reconfiguration and tardiness costs ($f_{c_s} = \sum(f_{m_s} + f_{t_s})$).

f_{m_s} represents the sum of total machine reconfiguration costs during the over the whole production schedule. Machine reconfiguration costs ($K_k^{\chi}(e, e')$) are linked to the change in a machine's configuration from time t to time $t+1$ ($\chi(k,t) \neq \chi(k,t+1)$) (11).

$$f_{m_s} = \sum_{t=0}^{T-1} \sum_{k=1}^{m} K_k^{\chi}\big(\chi(k,t), \chi(k,t+1)\big) \tag{11}$$

f_{t_s} represents the sum of tardiness costs of all jobs in the scheduling phase. Tardiness cost depends on the larger value between zero on the one hand, and the difference between completion time and due date on the other hand, multiplied by the penalty (12).

$$f_{t_s} = \sum_{i=1}^{n} W_i \cdot max(0, C_i - d_i) \tag{12}$$

This problem is subject to some constraints. First, manufacturing cannot take place during layout reconfiguration. Second, whenever there is a layout change between time t and t+1, operations must either complete before the change occurs ($C_i \leq t$), or start only after the reconfiguration time ($S_i \geq t + P^{\lambda}(u,u')$) corresponding to the transition from layout u to layout u' has elapsed (13).

$$\forall t \;\; \lambda(t) \neq \lambda(t+1) \Rightarrow \forall i \;\; (C_i \leq t) \vee \\ \vee \left(S_i \geq t + P^{\lambda}\big(\lambda(t), \lambda(t+1)\big)\right) \tag{13}$$

Similarly, when a machine configuration changes between t and $t+1$, no operations are executed on that machine during the reconfiguration. Therefore, all operations processed on machine k must either complete before the reconfiguration begins ($C_{ij} \leq t$), or start only after the machine reconfiguration time ($S_{ij} \geq t + P_k^{\chi}(e, e')$) corresponding to the transition from configuration e to configuration e' has elapsed (14).

$$\forall t \;\; \chi(\mu_{ij}, t) \neq \chi(\mu_{ij}, t+1) \Rightarrow (C_{ij} \leq t) \vee \\ \vee \left(S_{ij} \geq t + P_{\mu_{ij}}^{\chi}\left(\chi(\mu_{ij}, t), \chi(\mu_{ij}, t+1)\right)\right) \tag{14}$$

Machines can only process one operation at a time (15). No two jobs being executed on the same machine may overlap.

$$(i \neq i' \vee j \neq j') \wedge \mu_{ij} = \\ = \mu_{i'j'} \Rightarrow (C_{ij} \leq S_{i'j'}) \vee (C_{i'j'} \leq S_{ij}) \tag{15}$$

4.3 Partial sequential model: PP → L + S

In this subsection, process planning is solved and has as output data the machine/configuration that produces each operation. This data is used as input to the integrated problem of layout with scheduling (Figure 2).

The mathematical model of PP is exactly the same as in the previous section (Sequential model). The model of L + S is the integration of L and S as presented separately above. This yields equations 8, 9, 11, and 12 as the objective function, and equations 5, 7, 13, 14, and 15 as constraints.

4.4 Partial sequential model: PP + L → S

In this subsection, process planning and layout are first solved together and have as output data the machine/configuration for each operation, the layout for each job, and the sequence of operations for each job. This data is used as input to the scheduling (Figure 3).

The mathematical model that integrates PP and L

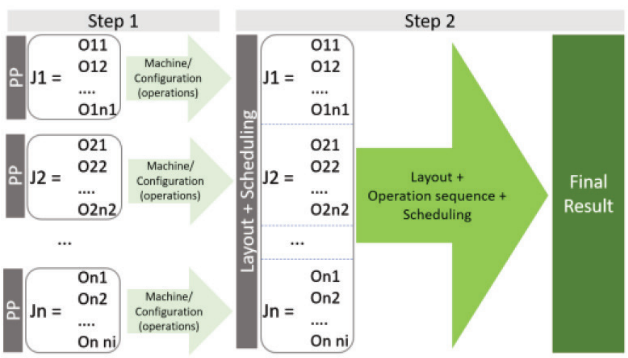

Figure 2. Partial sequential model: PP → L + S

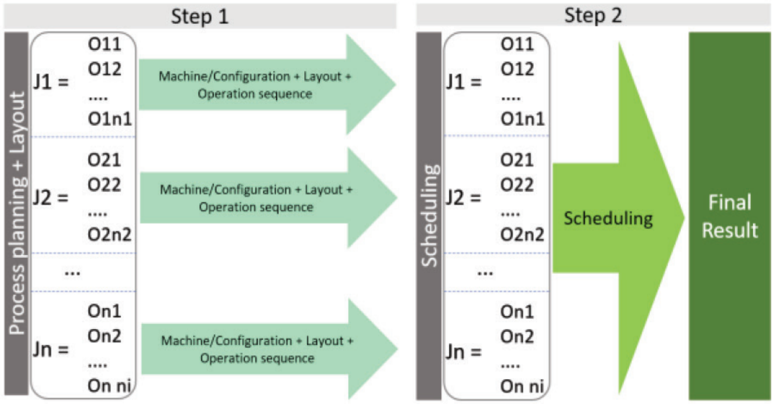

Figure 3. Partial sequential model: PP + L → S

is a mix of those presented in relation to the "Sequential model", with some minor changes. Previously, PP treated each job individually, but here they are treated together and no assumptions regarding the layout are necessary, since this is a decision variable. The objective function is composed of the equations 1, 3, 8 and 9, the first two of which must be considered for all jobs ($\forall i$). The constraints used are 4, 5, 6 (using $P^{\tau}_{\Lambda}(\mu_{ij}, \mu_{ij'})$), and 7.

4.5 Integrated model

This was first presented in Barros Garcia [30], the objective being to minimize the total cost, which is separated into five components: production costs (16), machine reconfiguration costs (11), layout reconfiguration costs (17), material handling costs, (18) and tardiness (12).

$$f_{p_I} = \sum_{i=1}^{n} \sum_{j=1}^{n_i} K_{ij} \left(\mu_{ij}, \chi_{ij} \left(\mu_{ij}, S_{ij} \right) \right) \tag{16}$$

$$f_{l_I} = \sum_{t=0}^{T-1} K^{\lambda} \left(\lambda(t), \lambda(t+1) \right) \tag{17}$$

$$f_{MH_I} = \sum_{i=1}^{n} \sum_{p=1}^{n_i - 1} K^{\tau} \cdot P^{\tau}_{\lambda\left(S_{i\sigma_i[p]}\right)} \left(\mu_{i\sigma_i[p]}, \mu_{i\sigma_i[p+1]} \right) \tag{18}$$

Decision variables are subject to the following constraints: 4, 5, 19 (an adaptation of 6), 7, 13, 14, and 15.

$$\sigma_{ij} + 1 = \sigma_{ij'} \Rightarrow C_{ij} + P^{\tau}_{\lambda(C_{ij})} \left(\mu_{ij}, \mu_{ij'} \right) \leq S_{ij'} \tag{19}$$

5. Exact methods

This section presents the exact methods used to solve the proposed problem. One way of obtaining the optimal result would be to go through all the possible combinations of the variable sets, which in practice is often not feasible because it would take too long. We therefore look to techniques that may reduce the search space and, consequently, the search time.

The present work proposes three exact methods: integer linear programming (ILP), constraint programming (CP), and constraint programming with a defined search strategy (CPS).

Integer linear programming (ILP) is one of the classical methods for mathematically modeling and solving optimization problems, where all variables belong to the set of integers, and all equations (objective function and constraints) are linear [32]. With a view to reducing the execution time required to obtain the best solution, we decided in addition to explore another exact technique, namely constraint programming (CP). CP is widely used in scheduling and resource allocation problems that have a combinatorial dimension. It involves exploring the domains of variables, where constraints are utilized to establish connections between variables and identify solutions that meet all specified constraints [33]. Efficiently narrowing down potential variable values is crucial for the effectiveness of CP. For this reason, we also decided to explore constraint programming with a defined search strategy specific to our global problem (CPS), in the hope of obtaining more promising results.

This section is focused exclusively on the strategy used in CPS, since ILP and CP are solved using respectively a standard IBM ILOG CPLEX Optimizer (based mainly on simplex algorithms) and IBM ILOG CP Optimizer software tools. CPS, on the other hand, uses the same software as CP, but combined with a specific search strategy. In the "Computational results" section below we compare some instance execution times using these different methods.

5.1 Constraint programming with search strategy (CPS) for the integrated model

The following decision variables are defined:

- μ_{ij}: the machine used for processing O_{ij};
- χ_{ij}: the configuration used for processing O_{ij};
- λ_{ij}: the layout used for processing O_{ij};
- σ_{ij}: the position of operation j in the process sequence among all operations in J_i;
- Φ_y: the (overall) position of operations in the process sequence among all operations, $y = \{1, \dots, \sum_{i=0}^{n} O_{i,n_i}\}$;
- S_{ij}: the start time of O_{ij}.

Once these decision variables have been set with CPS, a result may be obtained. The strategy that we developed for setting the variables consisted of the following steps, executed in the sequence outlined below:

1. Simultaneously set the machines and configurations (μ_{ij} and χ_{ij}) used for each operation, from the shortest processing time to the longest.
2. Set the layout (λ_{ij}) for each job, starting with the job's initial layout, which is always the first index ($l = 1$), and then in increasing index order.
3. Set the position of each operation (σ_{ij}) belonging to the same job, starting with the smallest possible position for each.
4. Set the positions corresponding to all operations (Φ_{ij}), respecting the previous step and fixing the operations of jobs with the earliest due date.
5. Finally, set the start time (S_{ij}) to the earliest possible time, respecting the overall position.

The aim behind our choices of search order was finding the most promising possibilities from the outset. For the first four items listed above (that is to say μ_{ij}, χ_{ij}, λ_{ij}, and σ_{ij}) two options are possible at each decision point in the decision tree: either to set the variable to a specific value, or not to do so (excluding the value from the set of possibilities). The only variable where there is not a decision point is start time (S_{ij}), and we set this to be as early as possible, shifting all scheduling to the left and shaving off any dead time.

6. Computational results

This section is divided into two parts: first, a comparison of the models presented in the "Model formulation" section above, and then a comparison of exact methods. To this end, a set of instances was randomly generated for the purpose of analyzing and comparing the performances of the methods described in the previous sections. The hardware used in each case was a laptop computer (16 Gb RAM, Intel(R) Core(TM) i7-8665U CPU @ 1.90GHz 2.11 GHz).

6.1 Comparing the models

In this subsection we compare results obtained from the four integer linear programming models presented above. Ten small instances were created to study how the models and methods behave. Columns 2 to 6 of table 4 show the main characteristics of each instance (number of jobs, operations, machines, configurations, and layouts), providing an overview of their scale. While some instances, such as instances 4 and 5, share the same main characteristics, they differ

Table 4. Comparing cost results with the different methods

Instance	NJ	NO	NM	NC	NL	PP - L - S	PP - L + S	PP + L - S	PP + L + S
1	3	2,2,2	3	2,2,2	2	44	44	49	42
2	3	3,2,2	3	2,2,2	2	59	59	59	56
3	3	3,2,2	3	2,2,2	2	58	58	56	52
4	3	3,2,2	3	3,2,2	2	148	140	148	79
5	3	3,2,2	3	3,2,2	2	76	76	91	70
6	3	3,3,3	3	3,3,3	2	58	56	56	52
7	3	3,3,3	3	3,3,3	2	95	90	125	73
8	2	3,2	3	3,3,2	3	54	54	54	33
9	2	3,2	3	3,3,2	3	35	35	36	35
10	2	3,2	2	3,2	3	35	35	37	35

NJ: number of jobs; NO: number of operations per job; NM: number of machines; NC: number of configurations per machine;
NL: number of layouts.

in other input data. These differing factors include costs and times of production, material handling, machine and layout reconfigurations, due dates, tardiness penalties, and precedence orders. Since we are focusing on small instances, these data were generated randomly and between a range of values of 1 and 15, except for precedence order which is Boolean. In addition, the last four columns of table 4 show the costs obtained with each of the models.

Even before analyzing the results, we were already able to predict that the results from the integrated model would be the best, since this model treats all parameters together and does not use assumptions. The central question is by how much these optimal results provided by the integrated model are superior to those of the other models.

In some cases (e.g., instances 9 and 10) the results are the same or very close. In other cases (e.g., instances 4 and 8), the results become noticeably worse, regardless of whether the model is sequential or partially sequential. When optimizing process planning, scheduling, and layout problems, it is crucial to recognize that achieving a 'good' solution in each individual problem does not guarantee an optimal overall solution. This is due to the inherent interconnections between these problems. For example, while optimizing the process planning for one job may lead to an optimal result in terms of costs and time for that job alone, this individual optimization may not be ideal for the final scheduling when multiple jobs require allocation and scheduling. Differences in results are therefore seen to be significant even for small instances, and such differences are likely to be magnified further in the case of larger instances, because of the number of variables and the size of the search space.

These results underline the advantages to be gained by integrating problems connected by their decision variables.

6.2 Exact methods

Our analysis having demonstrated the superiority of the integrated model, we shall from now on consider the integrated model only.

This subsection uses the same ten instances to compare CPLEX, CP, and CPS. Since all three methods are exact, they yield identical results after optimization. Therefore, for comparison, we will focus on their execution times rather than the costs, which are given in the last column of Table 4 for each instance and remain the same for all methods. Table 5 shows the instances and the execution times in seconds for each of them. The instances are not comparable, since they correspond to different examples. The purpose of Table 5 is to identify the most efficient method for the different instances.

When the execution time required to reach the optimal result exceeded 3000 seconds, execution was terminated. These cases are shown as “3000+” in Table 5. However, we also allowed them to run to completion on one occasion in order to know the optimal value.

Comparing CP with CPLEX, CP has significantly shorter execution times. However, instances 5, 6, 7, and 8 still take over 3000 seconds. Comparing CPS with the other two methods, the difference in execution time is plain to see. Most instances are solved in less than 20 seconds, although one instance nevertheless remains unsolved after 3000 seconds (instance 7).

Table 5. Execution times for the exact methods

Instance	NJ	NO	NM	NC	NL	CPLEX	CP	CPS
1	3	2,2,2	3	2,2,2	2	3000+	426	10
2	3	3,2,2	3	2,2,2	2	3000+	518	6
3	3	3,2,2	3	2,2,2	2	3000+	464	19
4	3	3,2,2	3	3,2,2	2	3000+	1430	35
5	3	3,2,2	3	3,2,2	2	3000+	3000+	8
6	3	3,3,3	3	3,3,3	2	3000+	3000+	164
7	3	3,3,3	3	3,3,3	2	3000+	3000+	3000+
8	2	3,2	3	3,3,2	3	3000+	3000+	4
9	2	3,2	3	3,3,2	3	1054	312	2
10	2	3,2	2	3,2	3	439	96	1

NJ: number of jobs; NO: number of operations per job; NM: number of machines; NC: number of configurations per machine; NL: number of layouts.

7. Industrial applicability

The model presented in this work has applications in different industrial contexts, for example, on assembly and disassembly lines. It is versatile enough to be applied to systems involving only machines, involving machines and humans, or involving humans exclusively.

The industrial-scale example described below is based on real data, with times, costs, and precedence graphs generated randomly for reasons of confidentiality. It is a scenario in which workstations remain fixed, while operators and tools are mobile. In accordance with our model, operators are regarded as machines, and reconfiguration times are linked to the movements of operators and tools.

In an industry that manufactures large pieces of kitchen equipment, two catalog products are manufactured in an area with 20 operators (considered as machines in the model presented in Section 4). These products have variants, including different colors and finishes. Product 1 has 12 operations, while Product 2 has 8. Operator can perform between two and four tasks, depending on their technical skills and training. There are five layout possibilities to consider. The objective is to produce five units within a specific period, comprising two units of Product 1 and three units of Product 2.

ILP and CP are unable to provide any solution in less than one hour (3600 seconds). For CPS the average cost obtained was 518 in one hour.

Each of the three individual problems is NP-hard; consequently, the integrated problem is NP-hard, forming an even larger combinatorial problem than each of them individually. The large amount of computation time entailed makes exact methods unsuitable for solving large instances. We note that in one hour, neither ILP nor CP was able to produce any result, not even an unsatisfactory one. Although CPS is also an exact method, it is able to significantly reduce the search space and yield results within a reasonable time. However, achieving the exact solution remains unfeasible within a practical time limit.

8. Conclusions and future works

This paper proposed four models applicable in the context of RMS for solving the problems of process planning, layout design, and scheduling optimization, such as to minimize total cost. What distinguishes the four models is whether they address these three separate problems sequentially, semi-sequentially, or jointly. A numerical analysis demonstrated the high superiority of the integrated model that addresses the problems jointly. Three exact methods (ILP/CPLEX, CP, and CPS) were then applied to this integrated model and a comparison was made. Finally, an industrial-scale problem was proposed.

The choice to solve the problems jointly is motivated by the variables that they have in common. When the problems are addressed sequentially and separately, the outcome will often be at some distance from a global optimum, since a good result individually does not necessarily lead to a good global result. The advantages of integrating process planning and scheduling have already been highlighted in previous research, as in Dou [23]. The importance of adding the layout problem is mainly due to the significant impact of material handling on total final cost [2]. An RMS may include highly automated machines, Automated Guided Vehicles to move products and machines, and other cutting-edge technologies, and in such cases including the layout is fundamental. It is also possible to use the models such that operators are considered to be machines. In this case, the movements of machines in the model correspond to the movements of operators. The models therefore have a wide applicability.

Our work presents two significant contributions. First, to our knowledge this is the first study to compare the cost differences between a sequential and an integrated model, such a comparison not so far having been made even in works that focus on two problems only. Second, we demonstrate that with an exact method and a robust search strategy, execution times can be significantly improved, yielding results even for large instances. In doing so, we have illustrated the method's potential effectiveness in relation to real instances.

The fact remains, however, that despite the superior performance of CPS, exact methods are not the most suitable for these types of problems because of their complexity (NP-hard). For future research, our objective is to introduce non-exact methods, including new heuristics or metaheuristics, potentially using CPS. For example, CPS can be used to calculate the fitness function of the metaheuristic. Alternatively, the metaheuristic can be hybridized, including a local search for which CPS can be used. To calculate the fitness function, it is important to determine whether CPS is better than a greedy algorithm in terms of computation time and memory use. Regarding the local search, CPS appears more promising than an exhaustive search; however, it is also important to examine whether alternative methods might be more efficient. Changing the objectives may be desirable, and in particular including environmental and human objectives in the objective function. Another potential objective could be to enhance the problem's complexity by removing assumptions or treating certain variables as stochastic. Treating specific variables as stochastic within the optimization model for RMS can be helpful, as it allows consideration of uncertainties intrinsic to dynamic production environments. This approach would make the model better able to adjust to changing conditions, such as fluctuating demand, machine breakdowns, or supply chain disruptions, resulting in more resilient and adaptable scheduling and planning strategies. In any case, all of the future changes that we envisage are likely, to a greater or lesser extent, to be useful in a variety of specific applications.

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