Universidad Autónoma de Nuevo León

Facultad de Ingeniería Mecánica y Eléctrica

Subdirección de Estudios de Posgrado

Flexible Jobshop Scheduling Problem with Resource Recovery Constraints

Tesis presentada por

Jobish Vallikavungal Devassia

como requisito parcial para obtener el grado de

DOCTOR EN INGENIERÍA

con Especialidad en Ingeniería de Sistemas

julio 2017

Universidad Autónoma de Nuevo León

Facultad de Ingeniería Mecánica y Eléctrica

Subdirección de Estudios de Posgrado

Flexible Jobshop Scheduling Problem with Resource Recovery Constraints

Tesis presentada por

Jobish Vallikavungal Devassia

Como requisito parcial para obtener el grado de

DOCTOR EN INGENIERÍA

con Especialidad en Ingeniería de Sistemas

julio 2017

Universidad Autónoma de Nuevo León

Facultad de Ingeniería Mecánica y Eléctrica

Subdirección de Estudios de Posgrado

Los miembros del Comité de Tesis recomendamos que la Tesis "Flexible Job-shop Scheduling Problem with Resource Recovery Constraints", realizada por el alumno Jobish Vallikavungal Devassia, con número de matrícula 1757843, sea aceptada para su defensa como opción al grado de Doctor en Ingeniería con Especialidad en Ingeniería de Sistemas.

El Comité de Tesis

[illegible]

Dra. María Angélica Salazar Aguilar

Directora

[illegible]

Dr. Vincent André Lionel Boyer

Co-Director

Jania Astrid saucedo

Dra. Jania Astrid Saucedo Martínez

Revisor

[illegible]

Dr. Francisco Román Angel Bello Acosta

Revisor

[illegible]

Dra. Iris Abril Martínez Salazar

Revisor

Vo. Bo.

[illegible]

Dr. Simón Martínez Martínez

Subdirector de Estudios de Posgrado

San Nicolás de los Garza, Nuevo León, julio 2017

To my parents Devasiya and Annamma

to my affectionate brother Aneesh and lovely sister Shancy

to all my relatives

and to all those friends who have been with me during the storm and calm.

Contents

List of Figures

List of Tables

Acknowledgements

I am grateful to my dissertation supervisors, Prof. María Angélica Salazar Aguilar and Prof. Vincent André Lionel Boyer, for their insight, guidance, and encouragement to make this work possible, and for the friendship, we made during this time. Thanks to the members of my dissertation committee, for their contributions, comments, and advice, that significantly improved the quality of this research. I am very grateful to all those who have, in one way or another, contributed to this research. I thank each of the faculty members and fellow graduate students of the Graduate Program in Systems Engineering at Universidad Autónoma de Nuevo León, for all those unforgettable moments we have had.

I remember all of my friends who welcomed and helped me to have a wonderful start in Monterrey, both in academic and social life. Arthur, César Arturo, Pedro Inés, Olga Lineth, Mayela Estefania, Cristian Hernández, and Naohito Yamada are some of them. I thank them for giving me memorable moments in my life and my stay here in Monterrey such an exceptional experience. I am deeply grateful to my precious treasure, my family, with those who I shared the most special and exciting moments. Above all, I thank God for giving me the willingness, skills, and an opportunity to achieve my goals.

Last but not least, my research work would not have been possible without a doctoral fellowship from Consejo Nacional De Ciencia Y Tecnología (CONACyT) with grant number 385986, Universidad Autónoma de Nuevo León (UANL), and from the Facultad de Ingeniería Mecánica y Eléctrica (FIME) at UANL. Additionally, my participation in some national and international conferences was supported by FIME-UANL and OPTISAD. Once again, I express my sincere gratitude to all of them to achieve my doctoral degree.

Summary

Jobish Vallikavungal Devassia.

Ph.D. candidate in Engineering with a Specialization in Systems Engineering.

Universidad Autónoma de Nuevo León.

Facultad de Ingeniería Mecánica y Eléctrica.

Title of the study: Flexible Jobshop Scheduling Problem with Resource Recovery Constraints.

Number of pages: 92.

Objectives and methods of study: The general objective of this research is to study a scheduling problem found in a local brewery. The main problem can be seen as a parallel machine batch scheduling problem with sequence-dependent setup times, resource constraints, precedence relationships, and capacity constraints.

In the first part of this research, the problem is characterized as a Flexible Job-shop Scheduling Problem with Resource Recovery Constraints. A mixed integer linear formulation is proposed and a large set of instances adapted from the literature of the Flexible Job-shop Scheduling Problem is used to validate the model. A solution procedure based on a General Variable Neighborhood Search metaheuristic is proposed, the performance of the procedure is evaluated by using a set of instances adapted from the literature.

In the second part, the real problem is addressed. All the assumptions and constraints faced by the decision maker in the brewery are taken into account. Due to the complexity of the problem, no mathematical formulation is presented, instead, a solution method based on a Greedy Randomize Adaptive Search Procedure is proposed. Several real instances are solved by this algorithm and a comparison is carried out between the solutions reported by our GRASP and the ones found through the procedure followed by the decision maker. The computational results reveal the efficiency of our method, considering both the processing time and the completion time of the scheduling. Our algorithm requires less time to generate the production scheduling (few seconds) while the decision maker takes a full day to do it. Moreover, the completion time of the production scheduling generated by our algorithm is shorter than the one generated through the process followed by the decision maker. This time saving leads to an increase of the production capacity of the company.

Contributions: The main contributions of this thesis can be summarized as follows: i) the introduction of a variant of the Flexible Job-shop Scheduling Problem, named as the Flexible Job-shop Scheduling Problem with Resource Recovery Constraints (FRRC); ii) a mixed integer linear formulation and a General Variable Neighborhood Search for the FRRC; and iii) a case study for which a Greedy Randomize Adaptive Search Procedure has been proposed and tested on real and artificial instances.

The main scientific products generated by this research are: i) an article already published: *Sáenz-Alanís, César A., V. D. Jobish, M. Angélica Salazar-Aguilar, and Vincent Boyer. "A parallel machine batch scheduling problem in a brewing company". The International Journal of Advanced Manufacturing Technology 87, no. 1-4 (2016): 65-75.* ii) another article submitted to the International Journal of Production Research for its possible publication; and iii) Scientific presentations and seminars.

Signature of the faculty advisers: [illegible]

Dra. María Angélica Salazar Aguilar

[illegible]

Dr. Vincent André Lionel Boyer

Resumen

Jobish Vallikavungal Devassia.

Candidato para obtener el grado de Doctor en Ingeniería con especialidad en Ingeniería de Sistemas.

Universidad Autónoma de Nuevo León.

Facultad de Ingeniería Mecánica y Eléctrica.

Título: Flexible Jobshop Scheduling Problem with Resource Recovery Constraints.

Número de páginas: 92.

Objetivo y metodología de estudio: El objetivo general de esta investigación es estudiar un problema de programación de producción que se identificó en una cervecería local. Este problema puede ser visto como un problema de programación por lotes en máquinas paralelas con tiempos de configuración dependientes de la secuencia, restricciones de recursos, relaciones de precedencia y restricciones de capacidad.

En la primera parte de esta investigación, el problema se caracteriza como un problema de programación flexible (tipo job-shop) con restricciones de recuperación de recursos. Se propone una formulación lineal entera mixta y se utiliza un gran conjunto de instancias adaptadas de la literatura del Flexible Job-shop Scheduling

Problem para validar el modelo. Se propone un procedimiento de solución basado en una metaheurística de tipo búsqueda de vecindarios variables (VNS), el desempeño del procedimiento se evalúa utilizando el conjunto de instancias adaptadas de la literatura. Los resultados computacionales muestran que el procedimiento propuesto es competitivo en cuanto a tiempo y calidad de las soluciones.

En la segunda parte, se aborda el problema real que se identificó en la empresa local. Se tienen en cuenta todos los supuestos y limitaciones a los que se enfrenta el tomador de decisiones en la cervecería. Debido a la complejidad del problema, no se presenta ninguna formulación matemática, sino que se propone un método de solución basado en un procedimiento voraz de búsqueda adaptativa aleatorizada (GRASP, por sus siglas en inglés). Varias instancias reales son resueltas por este algoritmo y se realiza una comparación entre las soluciones reportadas por el mismo y las encontradas a través del procedimiento seguido por el tomador de decisiones en la empresa. Los resultados computacionales revelan la eficiencia de nuestro método, considerando tanto el tiempo de procesamiento como el tiempo de finalización de la programación de la producción. Nótese que nuestro algoritmo requiere menos tiempo para generar la programación de producción (pocos segundos) mientras que el tomador de decisiones tarda un día entero en hacerlo. Por otra parte, el tiempo de finalización de la programación de producción generada por nuestro algoritmo es más corto que el generado a través del proceso seguido por el tomador de decisiones. Este ahorro de tiempo conduce a un aumento de la capacidad de producción de la empresa.

Contribuciones: Las principales aportaciones de esta tesis pueden resumirse de la siguiente manera: i) la introducción de una variante del Flexible Job-Shop Scheduling Problem, denominado como Flexible Job-shop scheduling problem with Resource Recovery Constraints (FRRC); ii) una formulación lineal entera mixta y una metaheurística de tipo búsqueda de vecindarios variables para el FRRC; y iii) el estudio del caso real para el cual se ha propuesto y probado un procedimiento voraz de búsqueda adaptativa aleatorizada en instancias reales y artificiales.

Los principales productos científicos generados por esta investigación son: i) un artículo ya publicado: *Sáenz-Alanís, César A., V. D. Jobish, M. Angélica Salazar-Aguilar, and Vincent Boyer. "A parallel machine batch scheduling problem in a brewing company". The International Journal of Advanced Manufacturing Technology 87, no. 1-4 (2016): 65-75.* ii) un artículo enviado a revisión para su posible publicación en el International Journal of Production Research; y iii) divulgación de los resultados en diversos foros científicos.

Firma de directores:: [illegible]

Dra. María Angélica Salazar Aguilar

[illegible]

Dr. Vincent André Lionel Boyer

Chapter 1

Introduction

Decision-making in manufacturing and service industries includes planning and scheduling as important processes in production, transportation, and distribution, among others. The planning and scheduling role in a company is to allocate limited resources to the activities to be done. This allocation of resources has to be done in such a way that the company optimizes its objectives and achieves its goals. Resources may be machines in a workshop, runways at the airport, crews at a construction site, or processing units in a computing environment. Activities may be operations in a workshop, take-offs, and landings at an airport, stages in a construction project, or computer programs to be executed. Each activity may have a priority level, an earliest possible starting time and/or a due date. Objectives can take different forms, such as minimizing the time to complete all activities, minimizing the number of activities after the committed due dates, and so on.

In the last years, there has been an explosive growth in the development and implementation of computer-based scheduling systems in the industry. In the case of planning and scheduling in manufacturing, orders that are released in a manufacturing setting have to be translated into jobs with associated due dates. These jobs often have to be processed on the machines in a work center in a given order sequence. The processing of jobs may sometimes be delayed if certain machines are busy. Preemptions may occur when high priority jobs are released which have to be processed at once. Unexpected events on the shop-floor, such as machine breakdowns or longer-than-expected processing times, also have to be taken into account, since they may have a major impact on the schedules. Developing, in such an environment, a detailed schedule of the tasks to be performed helps maintain efficiency and control operations.

In this research, two variants of scheduling problems are studied. Both can be seen like flexible job shop scheduling problems, however, different kind of constraints are taken into account. The first variant has been studied with theoretical purposes while the second one has been studied with practical reasons: solving a real case from a nationwide brewery. The main contributions of this work are the mathematical formulation for a flexible job-shop scheduling problem with resource recovery constraints and a metaheuristic to solve it. Additionally, a case study from a local brewing company has been carried out. The efficiency of the proposed solutions procedures has been shown on a large set of instances.

1.1 Motivation

In Mexico, beer production plays an important role given its significant contribution to the national economy. Mexican beer has high demand and constant growth, both in local and global markets. The annual report presented by National Brewers Association Craft Beer Market in Mexico 2015 illustrates the importance of beer in Mexico and its role in the Mexican economy. Moreover, brewing industry provides an outstanding number of direct and indirect jobs in Mexico. Figure 1.1 shows the major breweries in Mexico.

Official Mexican data shows that U.S. is the largest exporter of beer into Mexico, but it is mainly through large brands. According to the Mexican Brewers Association, craft beer market has expanded at 50% annual growth rate in the last ten years. For the fourth year running, Mexico was the world's leading beer exporter

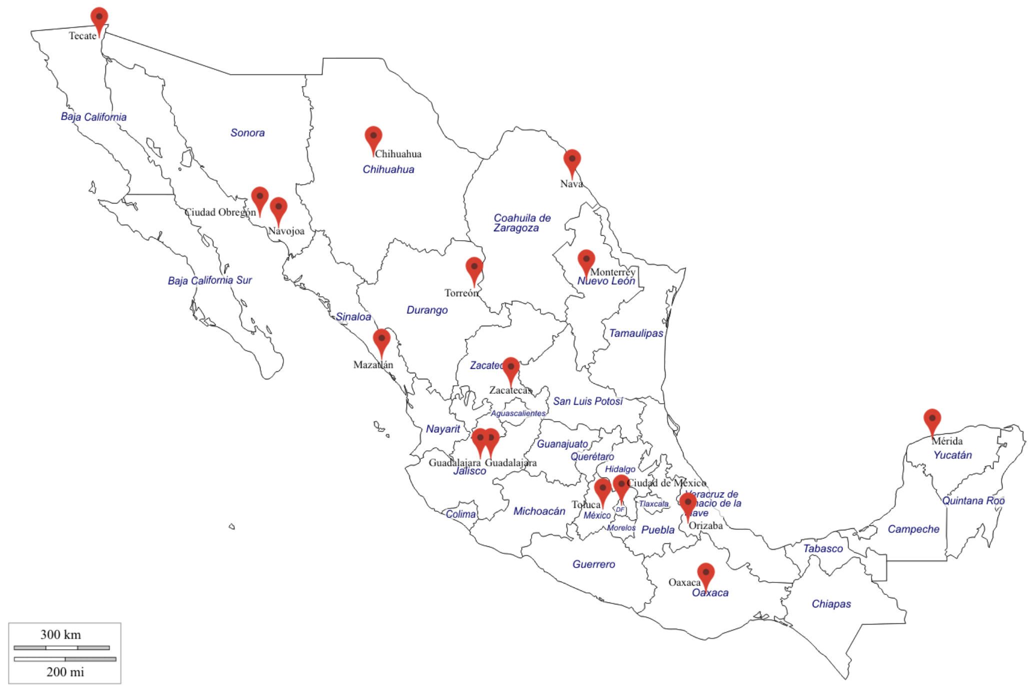


Figure 1.1: The breweries in Mexico

Source: *Geo-Mexico, the geography and dynamics of modern Mexico*

in 2014, $2.4 billion (17.9% of global beer exports). In 2013, Mexican beer exports reached a record of 2.2 billion dollars, a rise of 4.2% compared to 2012, and well ahead of both the Netherlands ($2.0 billion) and Belgium ($1.6 billion).

Mexico's breweries provide about 80,000 jobs directly and a further 800,000 indirectly. Total beer sales each year are worth as much as 20 billion dollars, and due to the high demands, both domestic and foreign, these sales constantly rise each year.

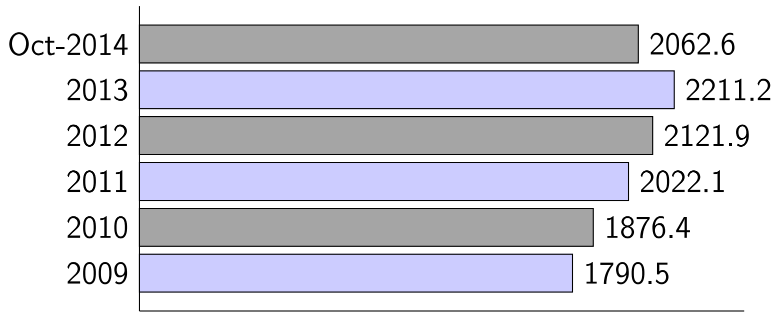


Chart 1.1: Mexican beer exports (million USD), 2009-2014

Source: *Banco de Mexico*

Based on South American Business Information (SABI), Mexico was the 6^{th} top beer producer in the world in 2014. In 2013, Mexico remained to be the top beer exporter for the fourth consecutive year. In that year, total beer exports reached 2.21 billion USD, representing 4.2% year-on-year rise and having 16.5% of the global beer market. For a better understanding, Chart 1.1 shows the income earned by beer exports, and Chart 1.2 illustrates a bar chart representation of beer exports of Mexico over some of the competitors in the global beer market.

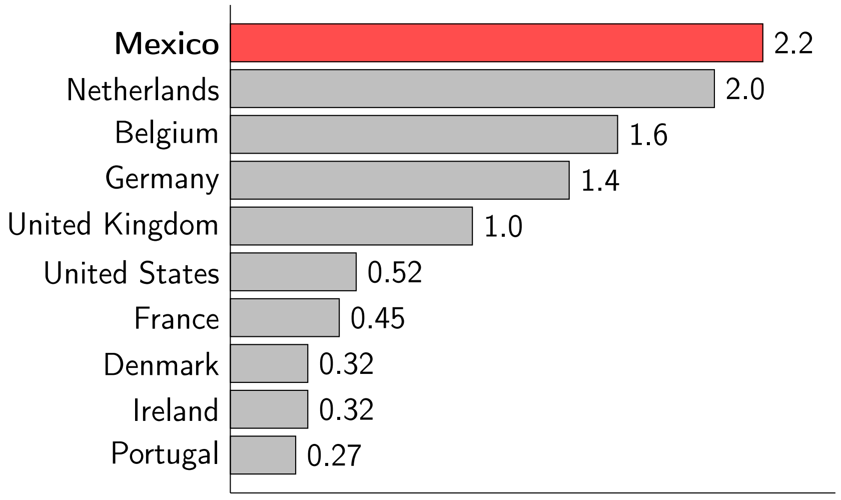


Chart 1.2: Total Beer Exports of Countries (billion USD), 2013
Source:*Economista*

Beer exports have been shown an increasing trend, from 1,790 million USD in 2009 to 2,211 million USD in 2013. Latest data show that by October 2014, beer exports totaled to 2,062.57 million USD, which was bigger than total beer exports in the same period in 2013 (1,872.72 million USD). An export and import balance of the Mexican beverage industry is shown in Figure 1.2. Due to this high exports of Mexican beer, and the influence of beer production in Mexican employment rate, the significant beer production can directly effect, the economy of Mexico.

One of the largest breweries in Mexico is located in Monterrey, Nuevo León. Hence, we established a relationship with the company and that allowed us to get insight into the brewing process. After multiple visits to the company, we observed that one of the hardest tasks in the company is the creation of the production schedule. That is the reason why we started this research work.

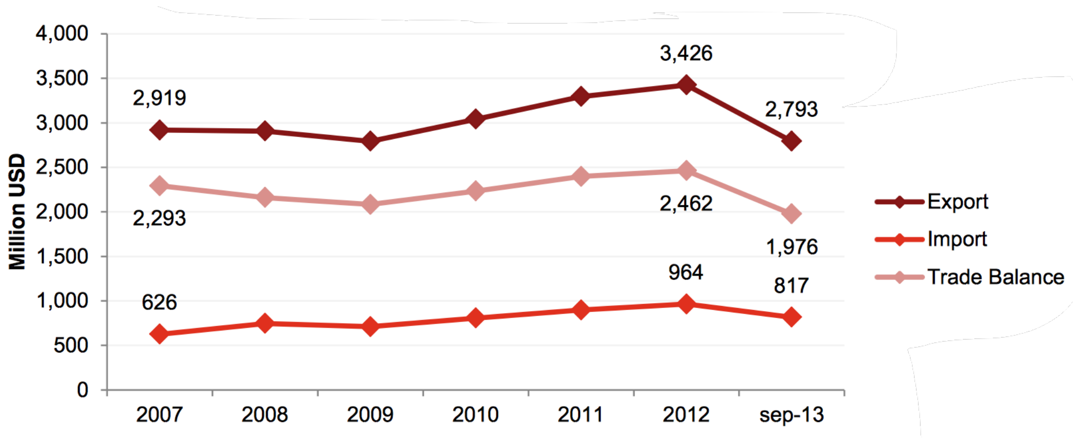


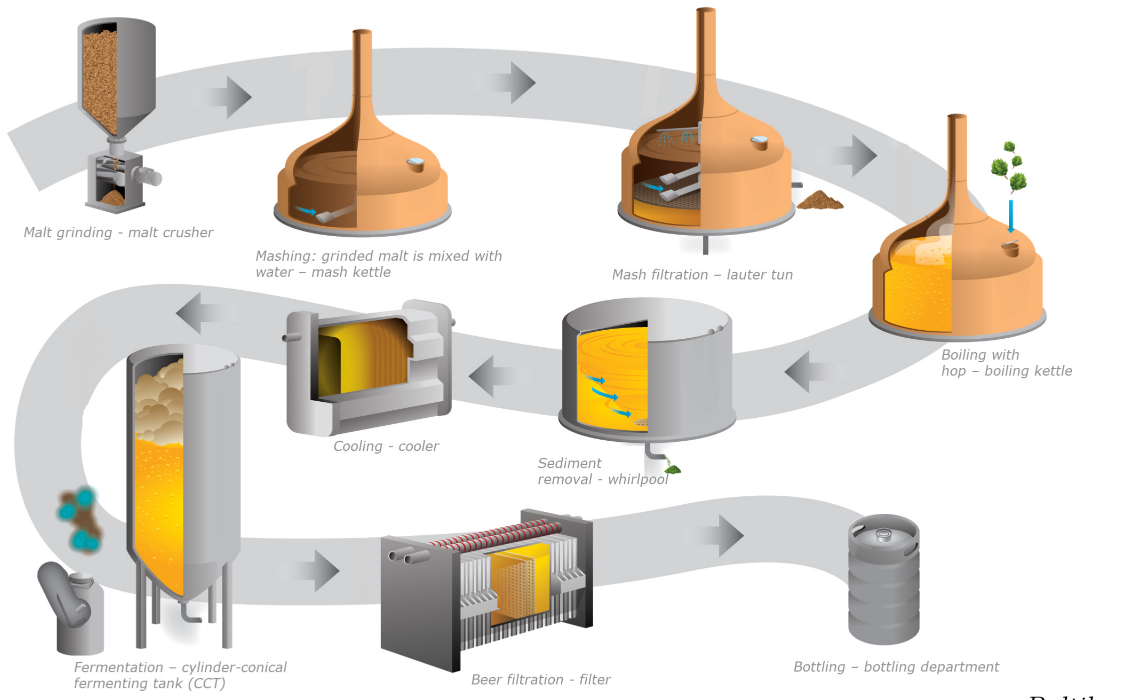
Figure 1.2: Trade Balance of the Mexican Beverage Industry

Source: *SE*

1.2 Problem statement

The planning and optimal production scheduling in the modern industry are very complex tasks. If we consider the brewing industry, the beer production needs exceptional attention because of a minor negligence leads to inferior products quality and significant productivity loss. It is practically impossible to make any small correction on the product since the errors may be realized only at the final stage of the production. Despite beer drawbacks, it has a significant role in social and economic growth in this twentieth century. Also, it is important to meet the customer orders by satisfying specific due dates. Thus, beer production needs an important consideration in production planning and handling. Figure 1.3 shows a typical production line and each stage of the production process in a brewery.

Inspired by this brewing process, we study two variants of scheduling problems. In the first one, we considered a flexible job-shop scheduling problem with a recovery time of resources. In the second one, we focused on the practical situation faced by the local company. Each variant is briefly described in the following subsections.


Malt grinding - malt crusher
Mashing: grinded malt is mixed with water – mash kettle
Mash filtration – lauter tun
Boiling with hop – boiling kettle
Cooling - cooler
Sediment removal - whirlpool
Fermentation – cylinder-conical fermenting tank (CCT)
Beer filtration - filter
Bottling – bottling department

Source: *Baltika*

Figure 1.3: Production line configuration in a brewery

1.2.1 Flexible Job-shop Scheduling Problem with Resource Constraints

Due to the recovery nature of the yeast used in the brewing process, we identified the recovery nature of resources which have not been widely studied in the Flexible Job-shop Scheduling Problems (FJSP) literature. In the FJSP multiple operations must be assigned to machines in sequence (respecting the order of operations in each job) such that the total completion time is minimized. The most common characteristics of the FJSP are the following: the number of jobs and the number of machines are known in advance; each job is composed of a fixed sequence of operations; there is certain compatibility between operations and machines; the processing time of an operations depends on the machine assignment, and any machine can process only one operation at a time.

In addition to the classical FJSP characteristics, we take into account the renewability and availability of resources. The resources are available in batches and the batch size and the recovery time of the resources depend on the resource type. Each operation may require a certain resource to be processed and during the production process the resources batch can be recovered once the entire batch of the resource is consumed. Then, the studied problem consists on assigning each operation to a compatible machine, by taking into account precedence relations between operations, resource requirements, compatibility and availability of resources and machines in order to minimize the makespan.

1.2.2 Scheduling problem in a brewing process

Scheduling of multiple products in parallel production lines, multiple stages of production, maintenance operations, and heterogeneous tanks makes the beer production scheduling a complex task. Moreover, the company produces various types of beers, and each beer type depends on the wort used.

There are three major stages in the brewing process: boiling, fermentation, and conditioning. During the boiling, all the ingredients are mixed and boiled to produce a particular wort which needs to be fermented. In the fermentation stage, multiple tanks can be used and each tank has a limited capacity, then we can start the boiling process of a wort, if and only if a fermentation tank is available. The conditioning stage is where the worts are conditioned and refined in order to obtain the final product. In our case, the conditioning phase is the bottling-and-packaging which has enough storage facility.

In order to maintain the quality of the products, we have to schedule cleaning operations regularly. These maintenance operations cannot be neglected and this condition leads to sequence-dependent setup times. The setup time depends on which wort is processing and which is going to be processed. Indeed, the frequency of these operations depends on the production sequence and the type of wort. The processing time and setup time in each machine are different since the machines are unlike and depend on the wort type. The process features specify that not all jobs can be processed by any machine, hence, there is a compatibility between machines and worts.

In this scheduling problem, the jobs to be scheduled are composed of a set of operations (worts). Each job is composed of only one wort type. The size of the job (batch) depends on the size of the fermentation tank that has been assigned to the job. A job can be seen as a batch of worts, whose size is not known a priori. Notice that, the boiling of worts from the same batch (job) can be split into the available boiling lines, but the fermentation of the entire job occurs in a unique tank. Moreover, the scheduling of each operation depends on the previous operation, due to the precedence constraints.

In this work, we focus on the scheduling of wort production, and we consider only the boiling and fermentation stages- the most critical stages in the brewing process. The key features of this problem are the existence of parallel machines, multiple stages of production, multiple products, batch production, and sequence-dependent setup times. Furthermore, the batches have different sizes, and the total number of batches are unknown. Detailed information can be found in Chapter 5.

1.3 Relevance

Scheduling and planning in the breweries are two important ways of decision-making which have a significant impact in productivity level of the company. Moreover, market researchers have shown that Mexican beer has a constant growth in market volume and value. Concerning total volume, it is expected to maintain sustained growth with a Compound Annual Growth Rate (CAGR) of 3% in the forecast period 2015-2020. As a result, sales of beer are expected to reach 7.6 billion liters in 2020. In 2013, the Mexican beverages market grew by 4.0% to 67.8 billion USD from the previous year (65.1 billion USD). Between 2013 and 2018, the market is forecasted to have a CAGR of 5.1% to reach the value of 87.1 billion USD in 2018. The market volume of Mexican beverage industry has been growing at a standard rate of 4.6%, since 2009. In 2013, the consumption volume of the country's industry grew 4.1% from 62.1 billion liters in 2012 to 64.6 billion liters. By 2018, it is expected to grow at a standard rate of 4.5% to reach 80.6 billion liters. Due to this high demand and low facilities, production scheduling is inevitable to maintain the high-quality product in minimum time and cost.

Since the operations research point of view, the scheduling process in the brewing company is similar to a variant of the classical Job-shop Problem (JSP). In the general JSP, n jobs have to be processed in m unrelated machines, with respect to the precedence relations, job-machine compatibility, and availability of machines. The general JSP is among the hardest combinatorial optimization problems since it is strongly NP-hard (Garey et al. [68]).

The FJSP is an extended version of the JSP by assuming that a job has to be processed by any of the compatible machines (Brucker and Knust [21]). Moreover, the classical FJSP involves two important decisions -the operation-machine assignment and the order in which the operations must be processed in the machines, such that the makespan is minimized. Thus, the FJSP is a much more complex version of the JSP, so the FJSP is strongly NP-hard and combinatorial (Mati and Xie [118]). Since the problem under study is an extended version of the FJSP, the complexity of the problem is NP-hard.

In the FJSP literature, several heuristics and metaheuristics have been proposed as solution procedures. However, to the best of our knowledge, none of the published work has addressed the scheduling problems we address in this work, which asserts the relevance of this thesis.

Besides, in modern industries, the primary cause of resource constraints could be machines, human resources, and raw materials. Machines do have certain limitations to process the operations. For instance, each machine can handle only one operation at a time, and each operation can be executed by at most one machine. Additionally, the execution of an operation can be restricted by the presence of scarce resources, which asserts the importance of the scheduling subject to the resource constraints. Moreover, the sequence-dependent setup time between operations and resource available in batches, as well as the renewability nature of resources are other complex features in modern industries, which we can see in this work.

In this thesis, we present a general FJSP problem and a case study from a local company. We propose a mathematical formulation for the FJSP with resource recovery constraints and a metaheuristic to solve it. For the case study, we propose a metaheuristic which has been tested on real data, the obtained solutions outperformed the scheduling generated by the expert in the company and the results have been published in *Sáenz-Alanís, César A., V. D. Jobish, M. Angélica Salazar-Aguilar, and Vincent Boyer. "A parallel machine batch scheduling problem in a brewing company". The International Journal of Advanced Manufacturing Technology 87, no. 1-4 (2016): 65-75.*.

1.4 Objectives

The objective of this research is to study a scheduling problem found in a brewing company and characterize it according to the existing literature. One goal is to represent the problem using a mathematical formulation and solve it by using the CPLEX optimizer, in order to obtain optimum solutions and determine the size of instances that can be handled by CPLEX. Another aim is to propose solution procedures based on metaheuristics like Greedy Randomized Adaptive Search Procedures (GRASP) and General Variable Neighborhood Search (GVNS). Finally, the performance of the proposed algorithms will be analyzed on a large set of artificial instances as well as on real instances.

1.4.1 Particular Objectives

i. Analyze the characteristics of the problem under study

ii. Classify and generalize the problem

iii. Define the problem and propose an efficient mathematical formulation

iv. Design and implement an instance generator for the problem under study

v. Validate the mathematical model using the CPLEX optimizer

vi. Characterize the problem under study and propose alternative solution procedures

vii. Evaluate the performance of the proposed algorithms on a large set of instances

viii. Compare the obtained results and analyze the problem nature

ix. Present preliminary results in scientific forums

x. Write and submit to revision the scientific articles derived from this work.

1.5 Organization

The content of this thesis is organized as follows: Chapter 2 presents a literature review related to our problems under study. Chapter 3 provides a detailed description and the proposed mathematical formulation of the flexible job-shop scheduling problem with resource recovery constraints. The proposed solution procedure and the analysis of results for the problem described in Chapter 3 are presented in Chapter 4. Chapter 5, contains a case study of the problem which is related to a real situation faced by a local brewing company (the solution procedure and the obtained results are also analyzed in this chapter). Finally, the main conclusions and future work are presented in Chapter 6.

Chapter 2

Literature review

Resource management is the most important decision of any scheduling problem. The most known resources are the machines (Gargeya and Deane [69], Figielska [64]) that will process the operations, but one can also consider the availability of the workforce, tools, or raw materials. For instance, in the classical Resource Constrained Project Scheduling Problem (RCPSP) each operation requires certain units of resources to be processed; hence they might not be scheduled at their earliest starting time but later when the resources are available (Kolisch [93]). Due to the nature of the resources based on their availability, they are classified into four main categories: Słowinski [167] identified three categories of resources, i.e., renewable resources, nonrenewable resources, and doubly constrained resources; and later, Böttcher et al. [16] introduced partially renewable resources.

- A *renewable resource* has a limited availability, but it can be reused or recovered during the overall process. For instance, in most scheduling problems, machines are renewable resources since each machine can be assigned to another operation once the processing of the current one finishes.
- The *nonrenewable resources* can be used only once in the entire process. Hence, at the beginning, a certain amount of resources are available and it can be consumed throughout the planning horizon. For instance, in a car manufacturing

company, the paint used and the money spent for the car production are nonrenewable resources since their availability is limited and they cannot be reused.

- A *doubly-constrained resource* is both renewable and nonrenewable; that is, both usage and consumption are constrained. For instance, human resources are renewable since when an employee finishes a job, he can be assigned to another job, but the total working hours that can be assigned to an employee within a week is limited.
- *Partially renewable resources* are used to model resources whose availability changes over the planning horizon. For instance, the staff availability in a university varies at each hour depending on the shifts; hence the employees are considered as partially renewable resources.

2.1 Resources in the Flexible Job-shop Scheduling Problem

The classical Flexible Job-shop Scheduling Problem (FJSP) was introduced by Brucker and Schlie [24], in terms of Multi-Purpose Machines (MPM job-shop problem), and it is a generalized form of the classical Job-shop Scheduling Problem (JSP) (Graham et al. [71]). The general JSP is strongly NP-hard as shown by Garey et al. [68]. In the FJSP, each job consists of a sequence of operations, and each operation has to be performed in order to complete the job. The execution of each operation has to be processed in one of the subsets of compatible machines. Then the problem is to define a sequence of operations together with the assignment of the starting time and the machine for each operation. Mati and Xie [118] have shown that the classic FJSP is NP-hard since it can be reduced to a JSP, by assuming that an operation can be processed by only one machine.

Traditionally, two kinds of approaches are widely used for solving the FJSP:

hierarchical and integrated approaches. The assignment of operations to machines and the sequencing of operations on the machines are treated separately in the former one, and the assignment and sequencing are done simultaneously in the latter one. Hierarchical approaches are based on decomposing the original problem in order to reduce its complexity. Brandimarte [19] was the first to use the hierarchical approach on FJSP, by solving a routing subproblem first and then the scheduling subproblem. Integrated approaches were introduced by Dauzére-Pérés and Paulli [47]. They extended the disjunctive graph representation of the FJSP in order to perform the machine assignment and the sequencing of the operations at the same time. Fattahi et al. [60] show that the hierarchical algorithms have better performance over the integrated ones. However, Vaessens et al. [178], Dauzére-Pérés and Paulli [47], Hurink et al. [83], and Gambardella and Mastrolilli [65] reported better results with integrated approaches, even though the solution complexity is higher.

The pioneer work of FJSP with resource constraints is due to Chan et al. [30] and is termed as Resource-Constrained FJSP (RCFJSP). The problem under study includes multiple flexible machines for the operations, fixture and tool constraints, and operation dependent setup times. In particular, an operation of a job can be processed on a machine only if the associated fixture and tool are both available. Besides, it is assumed that all these resources, fixtures and tools, are renewable. Reference is also made to the work of Rajkumar et al. [148] and Karthikeyan et al. [88] who studied a similar problem. A GRASP algorithm is proposed in the former work, and a discrete firefly algorithm is adopted in the latter work as the solution procedure.

A flow shop scheduling problem with additional resources has been studied by Figielska [61]. The author studied two-stage flow shop scheduling problem with parallel machines, where preemption is permitted, and jobs use additional renewable resources apart from the machines in the first stage. All required resources are granted to the jobs for processing or resuming after preemption, and they are returned by the job on finishing the process. Other variants of this problem have been studied afterward by Figielska [62, 63, 64]. Later, Cheng et al. [37] studied the resource-constrained flow shop scheduling with separate resource recycling operations. It is a two-stage flow shop problem where, initially, a common resource pool is available. A job can be processed only if the machine and a certain amount of resources are available. At the end of the process, a reduced amount of the resources is returned.

Mati et al. [116] have modeled and solved a practical FJSP with blocking constraints. The jobs have to wait on the current machine if the next machine where the job is going to be processed is occupied. This approach yields to a different management of resources through this blocking process called blocking constraints (Hall and Sriskandarajah [74]), or the deadlock avoidance problem (Mati et al. [117]). Another variant of the FJSP is studied by Ortiz et al. [144], where multi-resource consumption is required for each operation. Besides, setup times and the times required to transfer the batches to the machines are also considered.

Mixed integer linear programming models for the FJSP have been proposed by Roshanaei et al. [152], Demir and İşleyen [55], Yulianty and Ma'ruf [194], and Shen and Yao [163]. Although, due to the complexity of the problem, mainly metaheuristics have been investigated. The most used metaheuristics include Simulated Annealing (SA) (Li et al. [106], Shao et al. [159]), Tabu Search (TS) (Zhang et al. [197], Li et al. [104], Bożejko et al. [18], Li et al. [105]), Genetic Algorithm (GA) (Li and Huang [101], Costa [42], Defersha and Chen [52], Zhang et al. [200, 196], Azzouz et al. [8]), Particle Swarm Optimization (PSO) (Huang et al. [82], Singh et al. [165], Rey et al. [150], Singh and Mahapatra [164]), Ant Colony Optimization (ACO) (Liouane et al. [109], Xing et al. [189]), Variable Neighborhood Search (VNS) (Huang et al. [82], Gao et al. [66], Li et al. [103], Tayebi Araghi et al. [174], Yazdani et al. [192], Lei and Guo [97], Bagheri and Zandieh [10], Gao et al. [66], Zhang et al. [195]), Greedy Randomized Adaptive Search Procedure (GRASP) (Rajkumar et al. [149, 148]), among others. A detailed review on the FJSP can be found in Chaudhry and Khan [32].

2.2 Resources in Other Scheduling Problems

In this section, we discuss the main contributions on scheduling problems with resource constraints. In Table 2.1 we present an overview of the related literature. The first column shows the author names and the second one the year of publication. The column 'Rr' refers to renewable resources, 'Nr' to nonrenewable resources, 'Dc' to doubly constrained resources, and 'Pr' to partially renewable resources.

Nonrenewable resources have limited availability in the entire project. Many of the works in the literature model the available money as the nonrenewable resource, (see Akkan et al. [1], Demeulemeester et al. [53], Nudtasomboon and Randhawa [142], Tareghian and Taheri [173]), with the objective of minimizing the production cost. Artigues et al. [7] generalize the notion of nonrenewable resources where a job can consume or produce such a resource. Each job needs a fixed number of units of nonrenewable resources at the starting time of its execution. If the resource requirement for a job is positive then the job consumes some units of the resource; and if the requirement is negative, then the job produces some units of the resource. Kolisch and Drexl [94] show that, in the case of RCPSP, nonrenewable resources may lead to an unfeasible problem, and with at least two nonrenewable resources, the problem is NP-hard. Extensive reviews on scheduling problems with nonrenewable resources can be found in Brucker et al. [20], Hartmann and Briskorn [76], and Orji and Wei [143].

A renewable resource can be used multiple times for the entire project duration. The most common renewable resources in the literature are the machines since a machine can be assigned to handle more than one operation, i.e. the machine availability is reset every time it finishes processing an operation. The renewable resources can also be found in scheduling problems in the form of tools, fixtures, labor force, raw materials, etc. As we can see in Table 2.1, many researchers worked on the RCPSP, FJSP, and their variants while dealing with renewable resources.

Author(s)	Year	*Nr*	*Rr*	*Dc*	*Pr*
Schnell and Hartl [156]	2017	x	x	-	-
Ba et al. [9]	2016	-	x	-	-
Li and Huang [101]	2016	-	x	-	-
Paksi and Ma'ruf [145]	2016	-	x	-	-
Zheng and Wang [201]	2016	-	x	-	-
Lei and Tan [98]	2016	-	x	-	-
Schnell and Hartl [155]	2016	x	x	-	-
Chakrabortty et al. [29]	2016	x	x	-	-
Xiong et al. [190]	2016	-	x	-	-
Hermel et al. [80]	2016	-	x	-	-
Almeida et al. [4]	2016	-	x	-	-
Li and Huang [101]	2016	-	x	-	-
Gao and Pan [67]	2016	-	x	-	-
Ortiz et al. [144]	2016	-	x	-	-
Beşikci et al. [11]	2015	x	x	-	-
Yazdani et al. [193]	2015	-	x	-	-
Li and Huang [100]	2015	-	x	-	-
Cheng et al. [35]	2015	x	x	-	-
Lei and Guo [97]	2014	-	x	-	-
Tayebi Araghi et al. [174]	2014	-	x	-	-
Naber and Kolisch [134]	2014	-	x	-	-
Van Peteghem and Vanhoucke [180]	2014	x	x	-	-
Bianco and Caramia [12]	2013	-	x	-	-
Yulianty and Ma'ruf [194]	2013	-	x	-	-
Colak et al. [40]	2013	-	x	-	-
Chen and Chyu [33]	2012	-	x	-	-
Wang and Fang [183]	2012	x	x	-	-
Lang and Li [96]	2011	-	x	-	-
Mati and Xie [120]	2011	-	x	-	-
Van Peteghem and Vanhoucke [179]	2010	x	x	-	-
Wong et al. [188]	2009	-	x	-	-
Chyu and Chen [39]	2009	-	x	-	-
Lova et al. [111]	2009	x	x	-	-
Mati and Xie [119]	2008	-	x	-	-
Jarboui et al. [85]	2008	x	x	-	-
Mika et al. [126]	2008	-	x	-	-
Sabzehparvar and Seyed-Hosseini [153]	2008	-	x	-	-
Voß and Witt [181]	2007	-	x	-	-
Buddhakulsomsiri and Kim [26]	2007	-	x	-	-
Buddhakulsomsiri and Kim [25]	2006	-	x	-	-
Zhu et al. [202]	2006	x	x	-	x
Figielska [61]	2006	-	x	-	-
Chan et al. [30]	2006	-	x	-	-
Lorenzoni et al. [110]	2006	-	-	-	x
Lova et al. [112]	2006	-	x	-	-
Alvarez-Valdes et al. [5]	2006	-	-	-	x
Mika et al. [125]	2005	x	x	-	-
Alcaraz et al. [2]	2003	x	x	-	-
Bouleimen and Lecocq [17]	2003	x	x	x	-
Heilmann [79]	2003	x	x	-	-
Neumann and Schwindt [137]	2002	x	x	-	-
Hartmann [75]	2001	x	x	-	-
Józefowska et al. [87]	2001	x	x	-	-
Ulusoy et al. [177]	2001	x	x	x	-
Heilmann [78]	2001	x	x	-	-
ElMaraghy et al. [59]	2000	-	x	-	-
Klein [91]	2000	-	x	-	-
Selle [158]	1999	-	x	-	-
De Reyck and Herroelen [50]	1999	x	x	x	-
Böttcher et al. [16]	1999	-	-	-	x
Dauzère-Pérès et al. [48]	1998	-	x	-	-
Sprecher and Drexl [168]	1998	x	x	x	-
Bianco et al. [13]	1998	-	x	-	-
Hartmann and Drexl [77]	1998	x	x	-	-
Schirmer and Drexl [154]	1998	-	-	-	x
Kolisch and Drexl [94]	1997	x	x	-	-
Mori and Tseng [131]	1997	-	x	-	-
Sprecher et al. [169]	1997	x	x	-	-
Nudtasomboon and Randhawa [141]	1996	x	x	x	-
Boctor [15]	1996	-	x	-	-
Kolisch et al. [95]	1995	x	x	x	-
Węglarz [186]	1981	-	-	x	-
Słowinski [167]	1981	x	x	x	-
Słowiński [166]	1980	x	x	-	-
Nelson [136]	1967	-	x	-	-

Table 2.1: Literature on Scheduling Problems with Resource Constraints

The most relevant works of the FJSP with resource constraints have been discussed in the previous section, hence, in the section, we will focus on the RCPSP and its variants.

Few works have considered only renewable resources in the context of RCPSPs. For instance, Bianco and Caramia [12], and Naber et al. [135] proposed a mathematical formulation for the RCPSP with scarce resources. Chyu and Chen [39] proposed a payment model for the RCPSP. In this model, the contractor receives a profit for each job processed before a predetermined due date, and a penalty otherwise. The authors propose several VNS algorithms for the solution of this problem. Later, Chen and Chyu [33] proposed a model that aims to minimize the payment risk failure during a project execution. A memetic algorithm (MA) (Moscato et al. [132]) and a metaheuristic based on the VNS (Mladenović and Hansen [127]) algorithm, i.e. the Double Variable Neighborhood Search (DVNS) algorithm (Chyu and Chen [39]), are presented as solution procedures. The concept of resilience on RCPSP is introduced by Xiong et al. [190], where operations have an uncertain duration. The resilience refers to the capacity of the schedule to absorb perturbation.

Recently, Naber and Kolisch [134] proposed and evaluated, four different discrete time model formulations for the RCPSP with flexible resource profiles. In this work, one discrete time system is commonly used for all activities and resources. Resources required by an operation are classified into three general categories, namely principal, dependent, and independent resources. In this context, the resource quantity of a dependent resource depends on the one of a principal resource. The resources that do not depend on any other resource are termed as independent resources.

Dual resources have been introduced to model the machine-labor assignment. A model and design of machine and labor limited production systems have been presented by Nelson [136], and is considered to be a seminal work on Dual Resource Constrained (DRC) scheduling problems. The model includes a statistical arrival process (time interval between successive arrivals of jobs) and processing facilities consisting of some machine centers and a labor force. The author also considers the relative efficiency of each worker at each machine. Likewise, ElMaraghy et al. [59] studied a production scheduling problem in dual resource constrained manufacturing systems and proposed a GA as a solution procedure. Jaber and Neumann [84] studied a DRC system to model the effects of human fatigue and recovery to avoid work overloading and injury to employees.

The dual resource constrained problem has also been studied in the context of JSP by taking into account resource constraints derived from both machines and workers. This problem is known as Dual Resource Constrained Job-shop Scheduling Problem (DRCJSP) (Treleven and Elvers [176]). The Extension Dual Resource Constrained Job-shop Scheduling Problem (EDRCJSP) is studied by Li and Huang [100]. In this problem, several batches of jobs need to be processed before a deadline on machines that can be operated by a set of workers with different efficiency. The authors proposed a hybrid method based on GA and ACO algorithm to solve the EDRCJSP, i.e. the Branch Population Genetic Algorithm (BPGA). This BPGA has also been used to solve the classical DRCJSP (see Li and Huang [101], Li et al. [102]).

As a combined version of FJSP and DRCJSP, Zheng and Wang [201], Yazdani et al. [193], Lei and Tan [98], and Paksi and Ma'ruf [145] studied the Dual Resource Constrained Flexible Job-shop Scheduling Problem (DRCFJSP). Lang and Li [96] considered the dual-resources as machines and workers. The authors present an algorithm that combines grey simulation technology and non-dominated sorting genetic algorithm-II (Deb et al. [51]) to solve the problem. Many solution procedures are proposed towards the solution of DRCFJSP: VNS (Lei and Guo [97]), SA and Vibration Damping Optimization (VDO) (Yazdani et al. [193]), GA (Paksi and Ma'ruf [145]), Knowledge Guided Fruit-fly Optimization Algorithm (KGFOA) (Zheng and Wang [201]), among others. Recently, Lei and Tan [98] studied DRCFJSP with multiple objectives and a novel local search with controlled deterioration (CDLS) was proposed to minimize the makespan and the total tardiness.

In certain scheduling problems, operations may need more than one resource to be performed. These problems are commonly known as Multi-Resource Constrained FJSP (Gao and Pan [67]) or Multi-Resource Constrained Scheduling Problems (Multi-RCPSP) (Huang et al. [81], Davis and Heidorn [49]). Demeulemeester and Herroelen [54], and Patterson and Roth [146] proposed, respectively, a branch-and-bound algorithm and an integer programming approach for the Multi-RCPSP. Dauzère-Pérès et al. [48] introduced the notion of resource flexibility, where for each operation a list of candidate resources is defined (see, for instance, Mati and Xie [119]). Almeida et al. [4] studied a Multi Skill Resource Constrained Project Scheduling Problem (MSRCPSP), where each resource, such as an employee, have a set of skills to perform certain operations.

Another variant of scheduling problems with resource constraints is the Multi-mode RCPSP (MRCPSP) (Talbot and Patterson [171]), in which each operation can be processed in one out of several execution ways, called modes. Each execution mode represents an alternative combination of resource requirements for an operation that can affect its processing time. For example, a job can finish with 10 employees in 10 days, while it can be done in only 6 days with 20 employees. Many authors presented mathematical models for the MRCPSP (see Schnell and Hartl [156, 155], Hermel et al. [80], Chakrabortty et al. [29], Beşikci et al. [11], Cheng et al. [35], and Naber and Kolisch [134]). A survey on multi-mode resources can be found in Hartmann and Briskorn [76] and Węglarz et al. [187].

Solution approaches for the MRCPSP with renewable resources include Branch and Bound (Sprecher and Drexl [168], Brucker et al. [22], Sprecher et al. [169], Kolisch et al. [95]), Branch and Cut (Zhu et al. [202]), GA (Ba et al. [9], Beşikci et al. [11], Van Peteghem and Vanhoucke [179], Lova et al. [111], Mati and Xie [119], Hartmann [75], Ulusoy et al. [177]), Local Search Heuristics (Wang and Fang [183], Kolisch and Drexl [94], De Reyck and Herroelen [50]), SA (Bouleimen and Lecocq [17]), PSO (Jarboui et al. [85], Zhang et al. [199]), and TS (Mika et al. [126]), among others. The most recent work on MRCPSP is due to Hermel et al. [80]. This research is motivated by a firm that develops container packing software for doors distribution at a cross-dock facility. The arrival times of the containers are programmed with the required resources such as human resources and machines. A methodological framework and various mathematical models are presented as solution procedures.

We also make reference to the work of Wong et al. [188], and Ba et al. [9] who studied the multi-mode scheme in the context of JSP and FJSP, respectively. Wong et al. [188] considered the case where each operation requires a fixture to secure the process on the machine and each operation requires a tool to be processed. The authors proposed two heuristic approaches based on GA and PSO. Ba et al. [9] proposed a new mathematical model for a multi-resource flexible job-shop scheduling problem (MRFJSP). Machines, warehouses, vehicles, and detection equipment are the resources in this problem.

The MRCPSP has also been considered with both renewable and nonrenewable resources. For instance, Beşikci et al. [11] proposed a heuristic based on GA for this problem and Cheng et al. [35] explored the difference between preemption, activity splitting, and non-preemptive activity splitting. Van Peteghem and Vanhoucke [180] presented an overview of the existing metaheuristics to solve the MRCPSP with both renewable and nonrenewable resources. Moreover, a new benchmark dataset is proposed by the authors.

As we have seen before doubly constrained resources, introduced by Słowinski [167], are limited both for each period and for the whole project. For instance, Węglarz [186] studied a project scheduling problem where the doubly constrained resource is used to represent the number of staff-hours per day or week. In the literature, most of the authors did not consider doubly constrained resources alone, but they are combined with other types of resources.

The MRCPSP is studied by many researchers with renewable, nonrenewable, and doubly-constrained resources together. Bouleimen and Lecocq [17] proposed a heuristic based on SA as the solution procedure. Ulusoy et al. [177] considered the cash out- and in-flows associated with the operations, where at the beginning of each operation there is a cost (out-flow), and payments are received at payment points (in-flow) during the process. The operations are to be scheduled such that the overall project does not exceed a given due date. De Reyck and Herroelen [50] proposed a local search based methodology, that divides the problem into two distinct phases: a mode assignment phase and a resource-constrained project scheduling phase with fixed mode assignments. Sprecher and Drexl [168] considered a branch-and-bound solution procedure for this problem.

When the availability of a resource changed at each period of the planning horizon, like timetabling and employees' shifts in universities, it is referred as the partially renewable resource as introduced by Böttcher et al. [16]. Alvarez-Valdes et al. [5] described some preprocessing techniques and develop a heuristic algorithm, based on Scatter Search, for project scheduling problems under partially renewable resources. Alvarez-Valdés et al. [6] presented heuristics based on GRASP and path relinking. Drexl et al. [58] introduced a generalized project scheduling model where precedence constraints, multiple modes of resources, and multiple resources requirement are considered. The authors presented different formulations based on the RCPSP model and an instance generator.

Finally, some authors studied the RCPSP considering the three different kinds of resource constraints: renewable, nonrenewable, and doubly resource constrained resources. Nudtasomboon and Randhawa [141] considered multiple objectives and developed an implicit enumeration technique as a solution procedure. Kolisch and Drexl [94] showed that the problem may lead to an unfeasible solution with at least two nonrenewable resources and hence the complexity of the problem is NP-complete. De Reyck and Herroelen [50] solved the multi-mode version of the problem by dividing the problem into two distinct phases: a mode assignment phase and a resource-constrained project scheduling phase with fixed mode assignments. Zhu et al. [202] presented a branch and cut algorithm with local branching, variable reduction techniques, cuts generation, and bound tightening in order to accelerate the convergence of the algorithm. Finally, Van Peteghem and Vanhoucke [179] presented a GA where operation splitting is allowed. The reader is also referred to the book of Brucker and Knust [21] that discusses various branch-and-bound algorithms and heuristic approaches for this problem.

Apart from these major classification of resources, there are some other less common variants that can be found in the literature. If the available amount of a resource is an arbitrary number from an interval, as the petroleum in a moving car, such resources are called continuous (or continuously divisible) resources (Weglarz [185], Schwindt and Zimmermann [157]). Some resources such as containers, tanks, or other storage facilities have to store final or intermediate products during the production process. Such facilities could be depleted and replenished over time. To represent these resources, Selle [158] proposed the notion of cumulative resources (see Neumann and Schwindt [137], Neumann et al. [138, 139], and Brucker and Knust [21]). Gargeya and Deane [69] termed the resources that improve the productivity of labor and machine as auxiliary resources, such as machine attachments and accessories, or equipment for transportation.

2.3 Batch scheduling problems in parallel machines

In many of the modern industries, the production process must be handled in batches. Due to the extensive literature on Batch Scheduling Problems (BSP) and the characteristics of our problem under study, we concentrate only on BSP on parallel machines. The other major characteristics of our problem under study are: sequence-dependent setup time (ST_{sd}) due to cleaning process between operations or other shutdowns during the process; family (f) of products due to the similar characteristics of the operations or products; resource (res) availability; and capacity (C) constraints of the machines. In Table 2.2, we present most of the related works, to the best of our knowledge, with their main characteristics. Apart from the works presented in the table, some other works can be found in the surveys of Potts and Kovalyov [147], Allahverdi et al. [3], Méndez et al. [124], Drexl and Kimms

[57], Graves [72], and Graham et al. [71], among others.

Author(s)	Year	ST_{sd}	f	res	C
Costa [42]	2015	-	-	-	-
Jia and Leung [86]	2015	-	-	-	×
Shen et al. [161, 162]	2013	×	×	-	-
Lozano and Medaglia [113]	2013	×	×	×	×
Cheng et al. [34]	2013	-	-	-	×
Wang et al. [184]	2012	-	-	×	×
Li and Yuan [107]	2010	-	×	-	×
Condotta et al. [41]	2010	-	-	-	-
Wang and Chou [182]	2010	-	×	-	×
Buscher and Shen [28]	2010	-	-	-	×
Buscher and Shen [27]	2009	×	×	-	-
Tang and Liu [172]	2009	-	-	-	-
Xu et al. [191]	2009	-	-	-	-
Zhang and Gu [198]	2009	×	-	-	-
Klemmt et al. [92]	2009	-	×	-	×
Chung et al. [38]	2009	-	×	-	×
Leung et al. [99]	2008	-	-	-	-
Mosheiov and Oron [133]	2008	-	-	-	-
Kashan et al. [89]	2008	-	-	-	×
Malve and Uzsoy [114]	2007	-	×	-	-
Mathirajan et al. [115]	2007	-	×	-	-
Dastidar and Nagi [45]	2007	-	-	-	-
Lin et al. [108]	2007	-	-	-	-
Crauwels et al. [43]	2006	×	×	-	×
Hall and Potts [73]	2005	-	-	-	-
Mendez and Cerdá [123]	2004	×	-	×	×
Chang et al. [31]	2004	-	-	-	×
Méndez et al. [122]	2000	×	×	-	×
Sung et al. [170]	2000	-	-	-	-
Brucker et al. [23]	1998	×	×	-	-
Mehta and Uzsoy [121]	1998	-	×	-	×
Kim et al. [90]	1997	-	-	-	-
Moon et al. [130]	1996	×	-	-	-
Ghosh [70]	1994	×	×	-	-
Cheng and Chen [36]	1994	-	-	-	-
Monma and Potts [129]	1993	-	-	-	-
Birewar and Grossmann [14]	1990	×	-	-	×
Monma and Potts [128]	1989	×	-	-	-
Dorsey et al. [56]	1974	-	-	-	-

Table 2.2: Batch production problems on parallel machines

From Table 2.2, one can see that only Lozano and Medaglia [113] meets all the major characteristics of our problem. The authors studied a problem found in an automotive safety glass manufacturing facility and proposed a two-phase heuristic with two evaluation criteria: total tardiness and machine utilization. Although they consider batches of different capacity, batch splitting is not allowed, and the number of batches is fixed, contrary to our problem. The products with same ballistic level belong to the same family, and the processing time depends on the family.

Crauwels et al. [43] studied a batch scheduling problem with parallel machines where the jobs are partitioned into families. The jobs that require the same processing facility belong to the same family. The authors proposed a heuristic, where a job sequence is constructed by repeatedly solving a knapsack problem for each machine.

Méndez et al. [122] proposed a two-step systematic methodology, batching and scheduling, for the scheduling of a single stage multi-product batch plant. The batches are of different sizes according to the customer order of each product. The authors (Mendez and Cerdá [123]) also studied a reactive scheduling problem with resource-constrained multistage batch facilities. They proposed a MILP framework to solve this problem where the goal is to update the current schedule when unforeseen events occur.

Mixed integer formulations have been proposed in the literature to represent some variants of batch production problems (see for instance Lozano and Medaglia [113], Cheng et al. [34], Wang et al. [184]). Many authors proposed heuristics for solving the BSP such as GA (Costa [42], Noroozi et al. [140], Kashan et al. [89], Malve and Uzsoy [114]), ACO (Cheng et al. [34]), TS (Shen et al. [160], Buscher and Shen [27]), SA (Costa [42], Wang and Chou [182], Kashan et al. [89]), VNS (Shen et al. [161, 162]), and GRASP (Lozano and Medaglia [113], Damodaran et al. [44]), among others.

Many authors address batch scheduling problems where job families play an important role. The diffusion and oxidation operations in the wafer fabrication process are studied by Klemmt et al. [92], and Malve and Uzsoy [114]. Due to the chemical nature of the process, it is impossible to process jobs with different recipes together in the same batch. Hence the jobs are classified into family accordingly. Scheduling of heat-treatment operations of steel casting is studied by Mathirajan et al. [115]. In this scheduling problem, the jobs (castings) are classified into a number of job families based on the alloy type. These families are further classified into various sub-families based on the type of heat-treatment operations required. In general, the notion of family is used to group jobs with similar requirements (tools operation sequence, processing times, etc). The reader is referred to the work of Shen et al. [162, 161], Li and Yuan [107], Buscher and Shen [27], and Brucker et al. [23] where families of the product are considered in the context of batch production systems.

In many of the parallel batch scheduling problems, capacity constraints are considered due to the limitations of machines. In this context, the batch size must be less than the capacity of the machine (Wang and Chou [182], Buscher and Shen [28], Chung et al. [38], Chang et al. [31]). For instance, Wang et al. [184] study a problem where the capacity constraint due to the fuel storage capacity of the machines is considered. In Kashan et al. [89], the limited capacity of the burn-in oven in a semiconductor manufacturing problem leads also to a capacity constraint. Machines with fixed capacity (Jia and Leung [86], Mehta and Uzsoy [121]), identical capacity (Cheng et al. [34]), or different capacities (Wang and Chou [182], Klemmt et al. [92]) have also been considered in the literature.

Due to the complexity of the parallel batch scheduling problems with capacity constraints, most of the researchers proposed heuristics to solve the problem. For instance, Jia and Leung [86], and Cheng et al. [34] proposed an ACO based meta-heuristic, Wang and Chou [182] used a GA and a SA, Klemmt et al. [92] used a VNS heuristic, Kashan et al. [89] proposed a Hybrid Genetic Heuristic (HGH) based on a batch-based representation, and Mehta and Uzsoy [121] presented a dynamic programming algorithm. Moreover, Mixed Integer Non-Linear Program (MINLP) (Torabi et al. [175]), and Mixed Integer Linear Programming (MILP)(Cheng et al. [34], Wang and Chou [182], Buscher and Shen [28]) representations can also be found in the literature.

Due to the pace of development and breadth of research, a truly comprehensive review is probably impossible, and certainly beyond the scope of this thesis. This literature review presents the major work related to our problems. The scheduling problems address in this thesis are based on a real situation found in a local brewery. We study this situation as a parallel batch scheduling problem with sequence-dependent setup time, family considerations, resource constraints, and capacity constraints. From this problem, we derived a flexible job-shop scheduling problem with renewable resources where the resources are renewed by batch. To the best of our knowledge, both of these problems have characteristics that have not been addressed in the literature.

Chapter 3

Scheduling problem with renewable resources

In this chapter, we study a variant of the FJSP where resource constraints and recovery time of resource batches are taken into account. This variant has been called as the Flexible job-shop scheduling problem with Resource Recovery Constraints (FRRC). In the FRRC, any operation may require some resources to be processed and these resources are available in a limited quantity. Once a batch of resources is depleted, it can be recovered; which induces a recovery time (dead time in the production line). Moreover, the processing time of each operation depends on the selected machine, and each machine can process a subset of operations. Thus the machines are known as 'dedicated machines'.

In order to provide a better idea about the studied problem, this chapter provides a brief description of the FJSP and the FRRC through two examples and presents the proposed mathematical formulation for the FRRC.

3.1 The classical flexible job-shop scheduling problem

The classical Flexible Job-shop Scheduling Problem (FJSP) consists of scheduling a set $J = \{j_i : i = 1, 2, 3, ..., n\}$ of n jobs on a set $M = \{m_i : i = 1, 2, 3, ..., m\}$ of m machines. A job $j \in J$ is composed of a set $O_j = \{o_{ji} : i = 1, 2, 3, ..., n_j\}$ of n_j operations. An operation o_{ji} can be processed by any of the machines m, such that $m \in M_{ji}$; $M_{ji} \subseteq M$ is the set of compatible machines for operation o_{ji}. The processing time p_{jim} of an operation o_{ji} depends on the machine m. Each machine m can process at most one operation at a time. The operations must be processed without preemption, i.e., the operations cannot be interrupted until the execution of the operation is completed. The sets of jobs and machines as well as the compatibility operation-machine are known in advance. Then, the problem is to assign each operation to a compatible machine and determine the sequence followed by the operations on those machines with the objective of minimizing the makespan.

3.1.1 Example of the classical FJSP

Consider a 2×3 FJSP, i.e., a FJSP with two jobs and three machines. Let J be the set of jobs, then $J = \{j_i : i = 1, 2\}$ and M be the machine set, $M = \{m_i : i = 1, 2, 3\}$. Job $j_1 \in J$ is composed by a set $O_1 = \{o_{1i} : i = 1, 2, 3, 4, 5\}$ of five operations, and job $j_2 \in J$ is composed by a set $O_2 = \{o_{2i} : i = 1, 2, 3, 4\}$ of four operations. Each operation o_{ji} has a candidate machine set M_{ji}, where the operation can be performed, with a certain processing time p_{jim}. The complete data of the candidate machine set, operation-machine compatibility, and processing time are shown in Table 3.1. If an operation cannot be processed in a machine (incompatible), we represent this by a '-' symbol corresponding to the machine.

For operation o_{21}, for instance, the candidate machine set M_{21} is $\{m_1, m_3\}$.

By referring to Table 3.1, it could be precisely understandable that operation o_{21} can be processed in m_1 with a processing time of 4 units, and in m_3 with 1 unit of processing time, and these times are represented by $p_{211} = 4$ and $p_{213} = 1$, respectively. Operation o_{21} cannot be processed in machine m_2, due to machine-operation incompatibility, and that is represented by a '-' symbol in the table.

Job	*Operation*	*Machine_id*		
		m_1	m_2	m_3
j_1	o_{11}	2	3	2
	o_{12}	3	1	-
	o_{13}	2	2	3
	o_{14}	3	-	2
	o_{15}	1	3	2
j_2	o_{21}	4	-	1
	o_{22}	3	2	2
	o_{23}	4	2	3
	o_{24}	1	3	-

Table 3.1: The 2×3 FJSP data

A feasible solution of the 2×3 FJSP, with the data given in Table 3.1, is shown in Figure 3.1 through a Gantt chart. The constraints that should be taken into account in the FJSP can be enlisted as:

i. Each job j has to be processed by following an operations order (precedence constraints). i.e., an operation o_{ji} cannot start if the previous operation o_{ji-1} has not finished;

ii. Each machine can perform at most one operation at a time;

iii. Assignment of operations has to be done over compatible and available machines;

iv. Each operation cannot be interrupted during its execution (non-preemption condition).

The objective is to find the schedule with the shortest makespan, i.e., the minimum time required to process all operations in the job-shop.

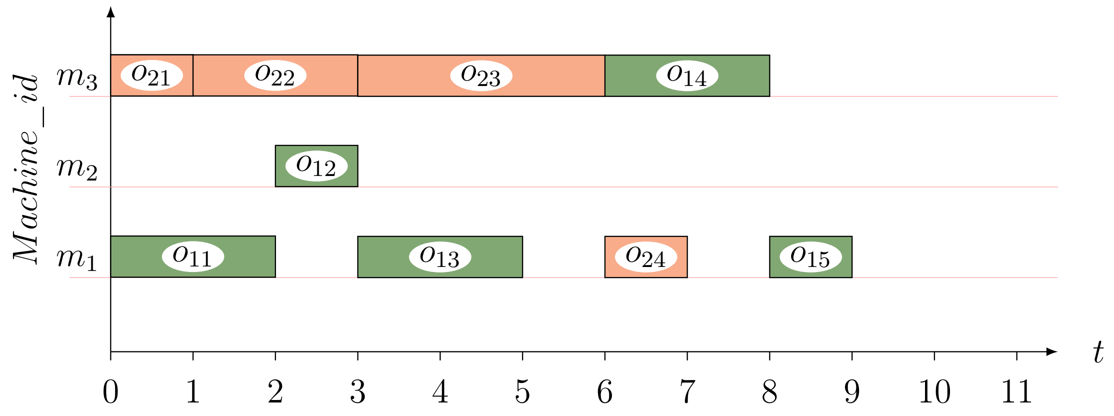


Figure 3.1: A solution representation of a classical FJSP based on the instance described in Table 3.1

As we have mentioned before, when we add the resource constraints to the classical FJSP, we obtain the FRRC.

3.2 THE FLEXIBLE JOB-SHOP SCHEDULING PROBLEM WITH RESOURCE RECOVERY CONSTRAINTS (FRRC)

Besides the classical constraints of the FJSP, in some of the existing industries, the operations may consume renewable resources. Suppose O_{jr} be the set of operations of job j that require the resource r to be processed. To start processing an operation, the required resources and a compatible machine must be available simultaneously. Notice that, some operations may not require renewable resources to be processed. Let R, be the set of available resources. A resource $r \in R$ is available in batches that contain b_r units of the same resource r.

Each batch of resources can be recovered with a recovery time τ_r, soon after the entire batch is completely consumed. Therefore, it can induce some dead time in the production line during the recovery process, i.e., between each batch of the same resource r.

Then, the problem is to assign each operation to a compatible machine and to determine its processing sequence on the machines by taking into account the availability of resources and machines in order to minimize the makespan. The resulting problem is called as the Flexible job-shop scheduling problem with Resource Recovery Constraints (FRRC). An example of the $2 \times 3 \times 2$ FRRC—an FRRC with 2 jobs, 3 machines, and 2 resources, is presented here, which is developed by adding FRRC constraints along with FJSP constraints that we have seen in section 3.1.1.

3.2.1 Example of the FRRC

Consider a $2 \times 3 \times 2$ FRRC with a set of two jobs, $J = \{j_i : i = 1, 2\}$, a set of machines, $M = \{m_i : i = 1, 2, 3\}$, and a set of resources $R = \{r_i : i = 1, 2\}$. Suppose that job j_1 has five operations and j_2 has four operations. The operation-machine compatibility, corresponding processing time, and resource requirements of the operations are shown in Table 3.2(a). One can see for instance that operation o_{12}, the second operation of job j_1, has the candidate set of machines $M_{12} = \{m_1, m_2\}$ with a processing time equal to 3 and 1, respectively, and which cannot be processed in machine m_3. Furthermore, operation o_{12} requires resource r_2, while operation o_{14} does not require any resource to be processed. Besides, the resource recovery time τ_r and batch size b_r are shown in Table 3.2(b).

(a) Operation-machine compatibility and resource requirements

Job	*Operation*	*Machine_id* m_1	m_2	m_3	*Resource*
j_1	o_{11}	2	3	2	r_1
	o_{12}	3	1	-	r_2
	o_{13}	2	2	3	r_1
	o_{14}	3	-	2	-
	o_{15}	1	3	2	r_2
j_2	o_{21}	4	-	1	r_2
	o_{22}	3	2	2	r_1
	o_{23}	4	2	3	r_2
	o_{24}	1	3	-	r_2

(b) Resource data

Resource id	r_1	r_2
Batch size	2	2
Recovery time	4	3

Table 3.2: A $2 \times 3 \times 2$ FRRC data

A feasible solution of the $2 \times 3 \times 2$ FRRC, based on Table 3.2 is presented in Figure 3.2 by means of a Gantt chart. Notice that the set of constraints involved in the FRCC are:

i. Each job j has to be processed by following an operations order (precedence constraints). i.e., an operation o_{ji} cannot start if the previous operation o_{ji-1} has not finished;

ii. Each machine can perform at most one operation at a time.

iii. Assignment of operations has to be done over compatible machines.

iv. Each operation cannot be interrupted during its execution (non-preemption condition).

v. An operation can be assigned to a machine, if and only if the machine and the required resource unit are available.

vi. The resource-operation allocation must not exceed the batch size, during any period.

vii. Before assigning the first unit of a resource batch, to any operation, there must be a recovery time of the previous batch, if any.

viii. Recovery time is effected from the starting time of the last unit of resource in a resource batch.

As in the FJSP, the objective of the FRRC is to find the schedule with the shortest makespan, i.e., the minimum time required to process all operations in the job-shop.

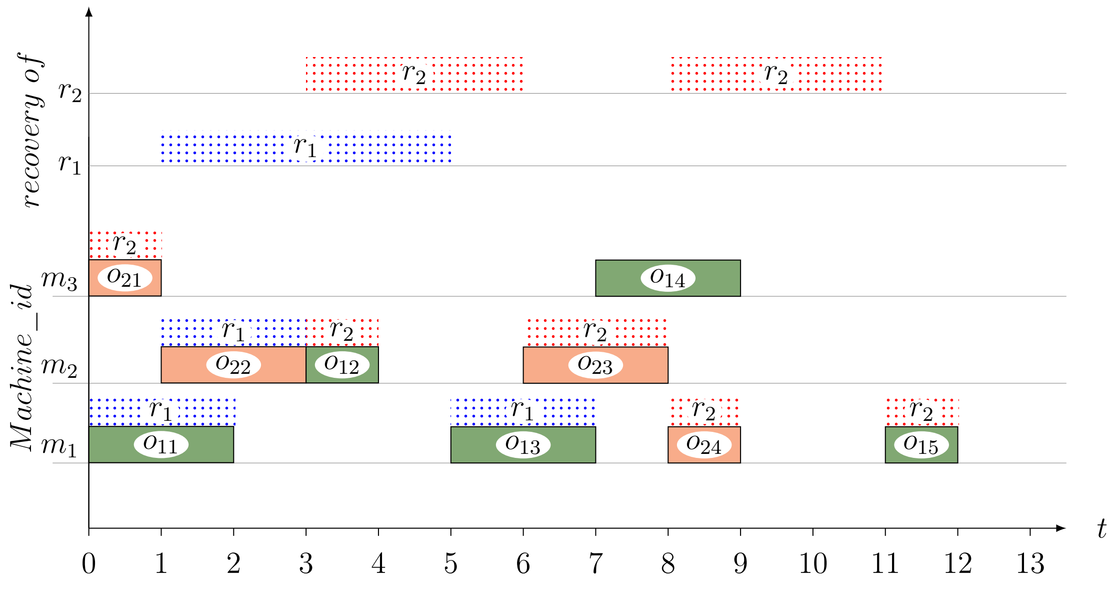


Figure 3.2: A solution representation of a 2×3 FRRC based on Table 3.2

In this Gantt chart, the operation-machine assignment and the operations sequence are presented along with a resource allocation and it is shown with a blue dot bar for r_1 and a red dot bar for r_2. For instance, consider an assignment of resource r_1, with batch size equal to 2, and a recovery time equal to 4 units, see

Table 3.2(b). The last unit of the first batch of resource r_1 is assigned to operation o_{22} which takes place at time 1. Thus, the next batch of resource r_1 is available for any other operation after the starting time of the operation o_{22}, at time 1, plus the recovery time (4 units of time), i.e.,r_1 will be available at time 5. So, during the period (1,5), where no units of resource r_1 is available, operations, that require r_1, cannot be processed. This unavailability of the resource is shown in a blue dots bar on the top of the chart, with name *recovery of* r_1. Hence, for this case, the next operation o_{13} can be assigned to any compatible machine, using resource r_1, at time 5. Even though the machine m_2 is available and the precedence operation o_{12} was completed at time 4, operation o_{13} cannot be assigned to any machine until resource r_1 is available. However, multiple operations can use the same type of resource while the size of the batch is not reached, for instance, operations o_{11} and o_{22} are using the same resource r_1, in the period (1,2), because the batch size of resource r_1 is equal to 2.

Moreover, the resources cannot be recovered by units but can be recovered by batches, and the recovery time of a batch starts soon after the assignment of the last unit of the resource. For instance, the recovery of the first batch of resource r_2 starts at time 3, and it is available for processing at time 6. The second batch of the same resource starts at time 8, and it is available for processing at time 11, since the batch size of resource r_2 is two, and the recovery time is equal to 3 units of time.

We have seen the complexity of the FJSP is $NP-hard$. The FJSP is a particular case of the FRRC, on the assumption that none of the operations require a resource to be processed. Thus, we can conclude that the FRRC is also $NP-hard$. Moreover, we represent this problem with a mixed integer linear programming model (MILP) which is described in the following section.

3.3 Mathematical formulation

The FRRC formulation is based on the one proposed by Roshanaei [151] for the FJSP.

The decision variables used in the mathematical model are the following:

$$x_{jilk} = \begin{cases} 1, & \text{if operation } o_{ji} \text{ is processed after operation } o_{lk} \\ 0, & \text{otherwise} \end{cases}$$

$$y_{jim} = \begin{cases} 1, & \text{if operation } o_{ji} \text{ is assigned to machine } m \\ 0, & \text{otherwise} \end{cases}$$

$$z_{ijrq} = \begin{cases} 1, & \text{if operation } o_{ji} \text{ is assigned to the } q^{th} \text{ unit of resource } r \\ 0, & \text{otherwise} \end{cases}$$

c_{ji}: completion time of operation o_{ji}

s_{ji}: starting time of operation o_{ji}

t_{rq}: starting time of the q^{th} unit of resource r

Using these decision variables, we then proposed the following formulation for the FRRC:

$$min\ C_{max} \tag{3.1}$$

$$\text{s.t.} : \sum_{m \in M_{ji}} y_{jim} = 1, \qquad \forall j \in J, 1 \leq i \leq n_j, \tag{3.2}$$

$$\sum_{j \in J} \sum_{i \in O_{jr}} z_{jirq} \leq 1, \qquad \forall r \in R, 1 \leq q \leq n_r, \tag{3.3}$$

$$\sum_{q=1}^{n_r} z_{jirq} = 1, \qquad \forall r \in R, j \in J, i \in O_{jr}, \tag{3.4}$$

$$c_{ji} \geq c_{j(i-1)} + \sum_{m \in M_{ji}} p_{jim} y_{jim}, \qquad \forall j \in J, i \in O_j, \tag{3.5}$$

$$c_{ji} = s_{ji} + \sum_{m \in M_{ji}} p_{jim} y_{jim}, \qquad \forall j \in J, i \in O_j, \tag{3.6}$$

$$c_{ji} \geq c_{lk} + p_{jim} - \mathcal{M}(3 - x_{jilk} - y_{jim} - y_{lkm}), \qquad \forall j < n, i \in O_j, l > j, k \in O_l, \; m \in M_{ji} \cap M_{lk}, \tag{3.7}$$

$$c_{lk} \geq c_{ji} + p_{lkm} - \mathcal{M}(x_{jilk} + 2 - y_{jim} - y_{lkm}), \qquad \forall j < n, i \in O_j, l > j, k \in O_l, \; m \in M_{ji} \cap M_{lk}, \tag{3.8}$$

$$t_{r(q-1)} \leq t_{rq}, \qquad \forall r \in R, 1 < q \leq n_r, \tag{3.9}$$

$$t_{r(q-1)} + \tau_r \leq t_{rq}, \qquad \forall r \in R, 1 < q \leq n_r, q \equiv 0 \; mod \; b_r, \tag{3.10}$$

$$s_{ji} \geq t_{rq} + \mathcal{M}(z_{jirq} - 1), \qquad \forall j \in J, i \in O_j, r \in R, 1 \leq q \leq n_r, \tag{3.11}$$

$$s_{ji} \leq t_{rq} + \mathcal{M}(1 - z_{jirq}), \qquad \forall j \in J, i \in O_j, r \in R, 1 \leq q \leq n_r, \tag{3.12}$$

$$c_{jn_j} \leq C_{max}, \qquad \forall j \in J, \tag{3.13}$$

$$s_{ji} \geq 0, \qquad \forall j \in J, i \in O_j, \tag{3.14}$$

$$t_{rq} \geq 0, \qquad \forall r \in R, 1 \leq q \leq n_r, \tag{3.15}$$

$$c_{ji} \geq 0, \qquad \forall j \in J, i \in O_j, \tag{3.16}$$

$$x_{jilk} \in \{0, 1\}, \qquad \forall j \in J, i \in O_j, l \in J, k \in O_l, \tag{3.17}$$

$$y_{jim} \in \{0, 1\}, \qquad \forall j \in J, i \in O_j, m \in M_{ij}, \tag{3.18}$$

$$z_{jirq} \in \{0, 1\}, \qquad \forall j \in J, i \in O_j, r \in R, 1 \leq q \leq n_r. \tag{3.19}$$

The constant $\mathcal{M}$ represents a big number. The objective (3.1) corresponds to the minimization of the makespan. Constraints (3.2) and (3.3) assure that each operation is assigned to one and only one machine and that each unit of resource is assigned to at most one operation, respectively. Since for each resource, we can compute the exact number of units necessary to process all the operations, each unit of resource will be assigned to at most one operation. The fact that each operation should consume exactly one unit of the required resource is modeled by constraints (3.4), and constraints (3.5) modeled the precedence relationship within the operations of a job. Linking the starting time of an operation with its completion time is modeled by constraints (3.6). Constraints (3.7) and (3.8) prevent the overlapping of operations processed on the same machine. Constraints (3.9) give priorities to the use of resource units in order to remove symmetries. Constraints (3.10) guarantee the recovery time between batches of the same resource. Constraints (3.11) and (3.12) synchronize the starting time of the operation with the one of its assigned unit of resource. Constraints (3.13) are related to the makespan. Constraints (3.14)-(3.19) state the nature of the variables.

This mathematical model has been implemented in C++ and solved by using the branch-and-bound method included in the IBM CPLEX Optimizer. The obtained results are discussed in Chapter 4.

Chapter 4

Solution procedure for the FRRC

In this chapter, we describe the proposed solution procedure for solving the FRRC as well as the validation of the model described in Chapter 3. The proposed solution procedure is based on a well-known metaheuristic called General Variable Neighborhood Search (GVNS). In the GVNS, the first component (shaking) is used to avoid local optima by randomly selecting a solution in a defined neighborhood of the best-known solution, then the second component (local search) improves the solution by exploring different neighborhoods. We designed five shaking procedures and five local searches based on different neighborhood structures. The neighborhood structures are explained with the help of diagrams in this chapter. Extensive computational tests have been carried out, on a large set of instances, in order to evaluate the performance of the proposed procedure. The analysis of the results obtained by the proposed GVNS is presented at the end of this chapter.

4.1 Variable Neighborhood Search

The idea behind Variable Neighborhood Search (VNS) is that distinct local optimal solutions are obtained by applying unlike neighborhood operators on the same solution. VNS exploits this aspect of the solutions by employing multiple neighborhood operators and it diversifies the search by allowing different neighborhood operators to explore different regions in the search space. Before applying VNS to a solution, a set of neighborhood operators $N = \{N_i : i = 1, 2, 3, \ldots, n_{max}\}$ must be defined, typically this set is ordered by increasing size of the neighborhood space. The set of solutions in the k^{th} neighborhood of x is denoted by $N_k(x)$. In the literature, several variants of the VNS have been proposed. In this research, we propose a General Variable Neighborhood Search (GVNS) which is an advanced form of the Basic Variable Neighborhood Search (Basic VNS).

4.1.1 Basic Variable Neighborhood Search

The steps involved in the Basic VNS are presented in Algorithm 1. Before starting the Basic VNS, it is needed to define a set of neighborhood structures and the stopping criterion of the procedure. There is a big number of stopping criteria used in the literature, such as the maximum CPU time allowed, maximum number of iterations, maximum number of iterations between two improvements, etc.

In the Basic VNS presented in Algorithm 1, k_{max} neighborhood structures are available. These neighborhood structures define neighborhoods around any solution $x \in X$, where X is the solution space. Then the local search is carried out over a randomly selected solution x' (shaking), which belongs to the neighborhood $N_k(x)$, ($k = 1$ initially), of x. After applying the local search routine over x', we obtain a local optimum solution x'' with cost $f(x'')$. Then three possibilities can occur:

i.) $x = x''$: then the procedure continues with the next neighborhood, i.e., $k \leftarrow k + 1$

ii.) $x \neq x''$ & $f(x'') \geq f(x)$: then the procedure is iterated with $k \leftarrow k + 1$

iii.) $x \neq x''$ & $f(x'') < f(x)$: then the procedure is restarted, $k = 1$, with the updated x.

Algorithm 1 Basic VNS

```
Input:
    $\{N_k; k = 1, \dots, k_{max}\}$ : Neighborhood structures
    $x$ : Initial solution
    $f(x)$: Local optimum of $x$
    A stopping criterion
Output:  $x$ initial solution
1: repeat
2:     $k \leftarrow 1$
3:     while $k \leq k_{max}$ do
4:         (a) Shaking: Select randomly a solution $x' \in N_k(x)$
5:         (b) Local search: Find the best solution $x''$ from $x$
6:         (c) Update solution: If $f(x'') < f(x)$ then $x \leftarrow x''$ and $k \leftarrow 1$; else $k \leftarrow k+1$
7:     end while
8: until Meet stopping criterion
9: return $x$
```

In case i), we iterate to the next neighborhood with $k \leftarrow k + 1$, because the best-found solution is the same as the incumbent solution. Therefore, we are no more interested in repeating the procedure with the same solution again and we continue with the next neighborhood. In case ii.), we obtain a different best solution in the neighborhood, but the local minimum value is worse than the one we have so far (the incumbent). Then, we would not continue with this solution, and we iterate to continue the exploration of the next neighborhood. Finally, in case iii.), we obtain a different solution and a local optimum that is better than that of the incumbent. In this case, the incumbent solution x is replaced by x'', and the search is restarted with the first neighborhood. The last neighborhood should be reached without a solution better than the incumbent one. The search is repeated at the first neighborhood $N_1(x)$ until a stopping criterion is met.

4.1.2 General Variable Neighborhood Search

The General Variable Neighborhood Search (GVNS) is a generalized version of the Basic VNS in which the simple local search is replaced by a set of local search structures, see Algorithm 2. The GVNS stops when none of the shaking procedures combined with the local search structures can improve the best-found solution.

Algorithm 2 General VNS

```
Input:
    $\{N_k; k = 1, \dots, k_{max}\}$ : Neighborhood structures for the shaking component
    $\{\overline{N}_l; l = 1, \dots, l_{max}\}$ : Neighborhood structures to be used in the local search
    $x$ : Initial solution by constructive heuristic
    $f(x)$: Local optimum of $x$
    A stopping criterion
Output: $x$ initial solution
 1: repeat
 2:    $k \leftarrow 1$
 3:    while $k \leq k_{max}$ do
 4:       (a) Shaking: Generate a solution $x'$ at random from the $k^{th}$ neighborhood $N_k(x)$ of $x$
 5:       (b) Local search:
 6:       $l \leftarrow 1$
 7:       repeat
 8:          Find the best solution $x'' \in \bar{N}_l(x')$
 9:          if $f(x'') < f(x')$ then $x' \leftarrow x''$ and $l \leftarrow 1$; else $l \leftarrow l + 1$
10:       until $l > l_{max}$
11:       (c) Update the best found solution: if $f(x'') < f(x)$ then $x \leftarrow x''$ and $k \leftarrow 1$; else $k \leftarrow k + 1$
12:    end while
13: until Meet the stopping criterion
14: return $x$
```

In order to solve the FRRC we designed a solution procedure based on the GVNS scheme. The detailed description of the proposed algorithm is provided in the following section.

4.2 Solution procedure for FRRC based on GVNS

The proposed GVNS starts with an initial solution x which is obtained through a constructive algorithm. The constructive algorithm can be seen in Algorithm 3. Notice that, the constructive algorithm is a greedy procedure where at each iteration the operation with the smallest release time is selected, and then it is assigned to the machine that leads to the earliest starting time. In our implementation, the release time of an operation is defined as its earliest starting time taking only into account the precedence constraints, and ignoring the machines and resources availability. If the assignment of an operation is not compatible with the precedence constraints, its release time is considered as infinity. The earliest starting time of an operation on a machine is computed according to the machine availability, and the resource recovery time of the required resource, if needed.

Once we have the initial solution x, reported by Algorithm 3, this solution is used to feed the GVNS (Algorithm 2). The stopping criterion is reached when the GVNS finds 10 consecutive non-improvement solutions. For a better understanding of the proposed algorithm, in the following subsections full details are provided.

4.2.1 Solution representation

In order to illustrate a solution and the neighborhood structures used in Algorithm 2, we represent a solution x as an array whose size corresponds to the total number

Algorithm 3 Constructive Algorithm

```
Input:
    $x$: An empty solution
    $\mathcal{O}$ : Set of operations to be assigned
Output: $x \leftarrow$ solution
1: while $\mathcal{O} \neq \emptyset$ do
2:     $o_{ji} \leftarrow$ operation with the smallest release time, where $o_{ji} \in \mathcal{O}, j \in J, i \in O_j$
3:     $\mathcal{O} \leftarrow \mathcal{O} \backslash \{o_{ji}\}$
4:     $m \leftarrow$ machine where $o_{ji}$ achieves the earliest starting time $t_{ij}$; $m \in M_{ji}$
5:     Assign $o_{ji}$ to machine $m$ at time $t_{ij}$ in $x$
6: end while
7: return $x$
```

of operations to be scheduled. Each cell of the array contains a triplet (j, o, m) where j represents the job index, o the operation index, and m the assigned machine index. Here we use only the indices of the job, operations, and machines, to ward off the intricacies of the solution array. For instance, $(2, 1, 3)$ refers to the assignment of operation one of job j_2 (o_{21}) to machine m_3. Consider the example that we saw in section 3.2.1. Here the total number of operations is 9, so the array size. A solution representation of the example is provided in Figure 3.2, and the array solution representation is shown in Figure 4.1.

(2,1,3)	(1,1,1)	(2,2,2)	(1,2,2)	(1,3,1)	(2,3,2)	(1,4,3)	(2,4,1)	(1,5,1)

Figure 4.1: Solution representation of Figure 3.2

From this solution array, it is possible to compute the starting time and the completion time of each operation through the greedy algorithm, where operations are assigned one by one, from left to right, in the solution array of the selected machine m. Indeed, the resource availability should be taken into account during this process.

Moreover, because of the precedence constraints within the operations of a job, the order of appearance of the operation is known. Thus, from the array representation shown in Figure 4.1, the operation o in a triplet (j, o, m) can be deduced from j and its position in the table. Then we know that the first time a job j appears in the array, it is associated with its first operation, the second time it appears, it is related to the second operation, and so on. Otherwise, we would have an unfeasible solution, due to the precedence constraints. This can be used to maintain feasibility when the positions in the array are changed with the neighborhood exploration, assuming that there is no conflict in the machine assignment.

4.2.1.1 The critical path and the critical block

In the neighborhood structures, we use the concept of the critical path and critical block. Consider the example that we have seen in section 3.2.1.

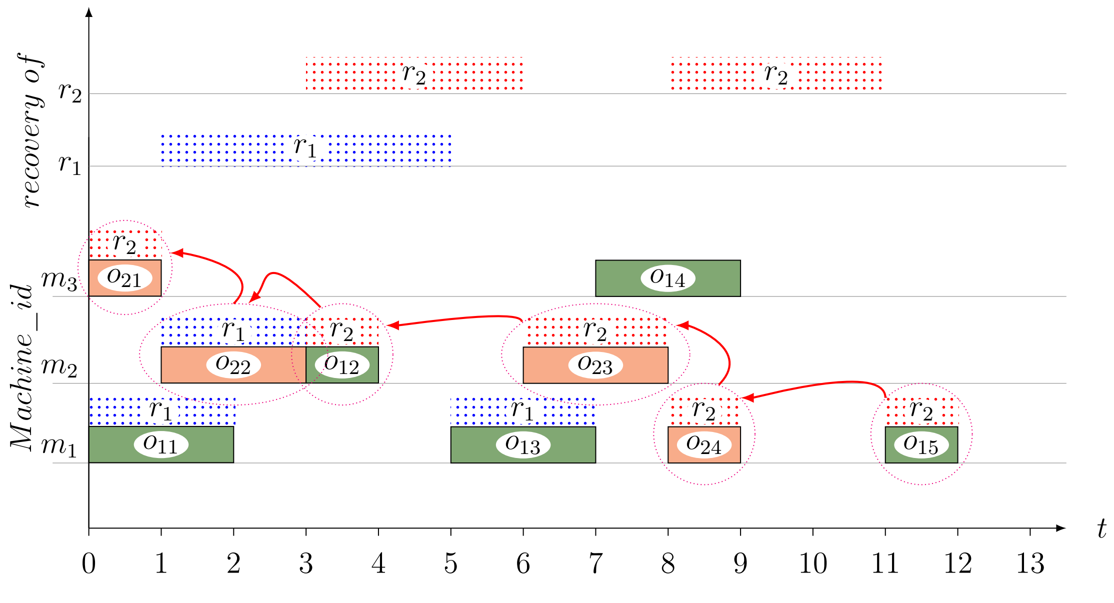


Figure 4.2: Critical path of the solution representation shown in Figure 3.2

Given a solution, its critical path is the sequence of operations that yields to the makespan value on that solution. For example, from Figure 4.2, the last completed operation is o_{15}. The reason why operation o_{15} has a delay is the unavailability of r_2, which has been used by o_{24}. Operation o_{24} is delayed due to the precedence constraint of operation o_{23}, which is delayed due to the unavailability of r_2 that has been used by o_{12}. Operation o_{12} is delayed due to the unavailability of machine m_2 and its precedence operation o_{22}, which is delayed due to the precedence relation with o_{21}. Thus, these operations together form a critical path. The formation of the critical path is illustrated using the red backward arrows and circles in Figure 4.2. Thus the operations $o_{15}, o_{24}, o_{23}, o_{12}, o_{22}$ and o_{21} together form the critical path of the current solution.

A block is a continuous sequence of operations in the critical path. Although we can use different criteria to define a block, here in our case, the operations that integrate the block are the consecutive operations that belongs to the critical path and are performed on the same machine. For example, from Figure 4.2, one can see that operations, o_{22}, o_{12}, and o_{23} are processing on the same machine m_2. So these operations form a block. Operations o_{24}, o_{15} are also processing on the same machine, m_1, hence they also form a block.

4.3 Neighborhood structures of the GVNS

As we can see in Algorithm 2, we need to define the neighborhood structures for both *shaking* and *local search* phases. We represent the k^{th} neighborhood of x in the shaking phase with $N_k(x)$, and the l^{th} neighborhood of a solution x in the local search phase by $\overline{N_l}(x)$. Indeed, shaking a solution x consists of selecting a random solution from one of its neighborhoods $N_k(x)$, $k = 1, ..., k_{max}$, and a local search on a solution x refers to finding the best solution in one of its neighborhoods $\overline{N_l}(x)$, $l = 1, ..., l_{max}$. Among all the neighborhoods we tested, we present here five neighborhoods for the shaking phase and five for the local search, which are the ones that appear to be the more efficient to solve the FRRC.

4.3.1 Neighborhood structures in the shaking phase

The shaking procedure allows to diversify the search and to escape from local optima, so the neighborhoods in the shaking phase must be of diverse nature as much as possible. The neighborhood structures used in the shaking are presented below, and throughout each of the neighborhoods, we refer as x to the current (incumbent) solution and x' as (resulting) one of its neighbor solutions.

4.3.1.1 N_1: Shifting a job in the critical path

Select two random triplets (j, o, m) and (j', o', m') from the critical path of the current solution x and shift job j to the next position of (j', o', m'). Then, update the operations according to their order of appearance in the array and keep the machine assignment in x' as it is in x.

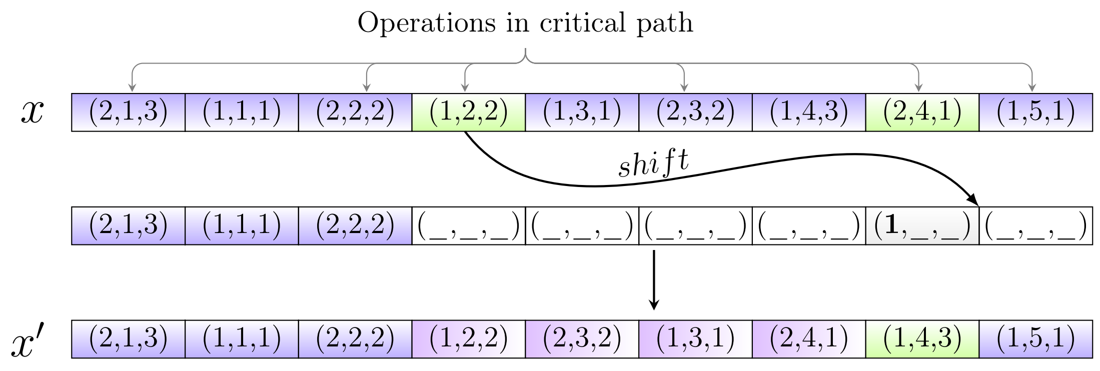


Figure 4.3: N_1: Shifting a job in the critical path

The move related to this neighborhood structure is shown in Figure 4.3. As one can see, for the given example, two random triplets, $(1, 2, 2)$ and $(2, 4, 1)$, have been selected from the critical path. Then, the job from the first triplet (1), is shifted to the next position of the second triplet $(2, 4, 1)$. After that, the operation indices between the triplets that have been chosen are updated by preserving the machine assignment as in the original solution x. Finally, we get a resulting solution x' which is a neighbor of x.

4.3.1.2 N_2: Swapping two jobs in the critical path

Choose two random triplets from the critical path of a solution x, namely (j, o, m) and (j', o', m'), respectively. Then, the job indices j and j' are swapped and the operations order in each position is updated between them, and the machine assignment is kept as in x. A schematic representation of this move is shown in Figure 4.4.

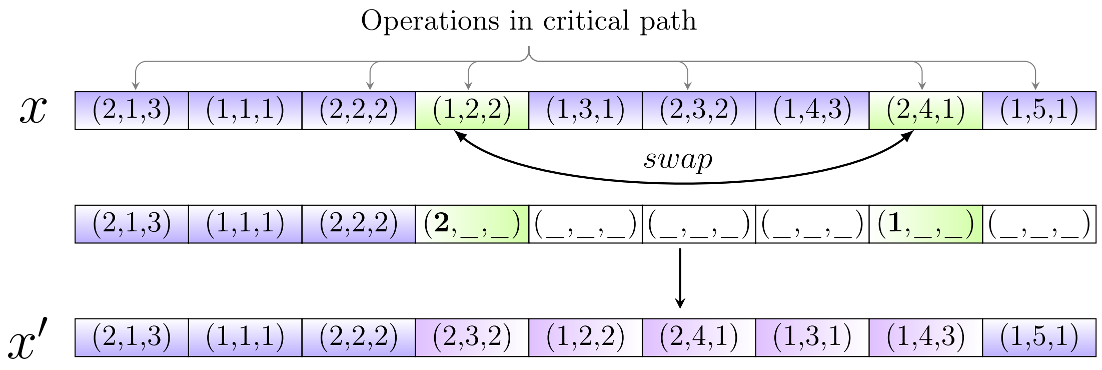


Figure 4.4: N_2: Swapping two jobs in the critical path

4.3.1.3 N_3: Swapping two jobs with machine reassignment

Two random triplets (j, o, m) and (j', o', m') are chosen from a solution x. Then, jobs j and j' are swapped and the operations order in each position are updated, while the machine assignment is kept as in x. Finally, the operations o_{jo} and $o_{j'o'}$ are reassigned to a different compatible machine selected at random. A schematic representation of this move is shown in Figure 4.5.

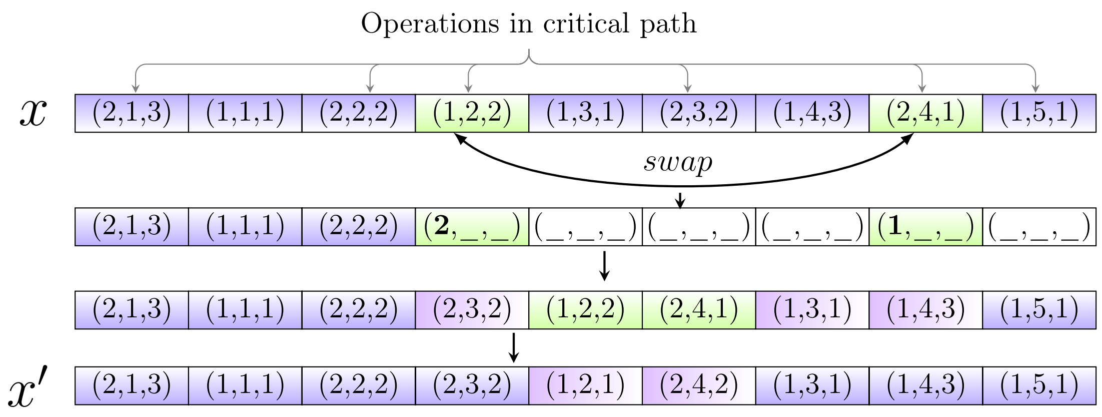


Figure 4.5: N_3: Swapping two jobs with machine reassignment

4.3.1.4 N_4: Shifting a job in the critical path with machine reassignment

Two triplets (j, o, m) and (j', o', m') are randomly selected from the critical path. Then the shifting movement of N_1 is applied, and operations o_{jo} and $o_{j'o'}$ are reassigned to a different compatible machine which is randomly chosen. This neighborhood is very similar to N_1.

4.3.1.5 N_5: Shifting a job and reassigning to a different machine

Two random triplets (j, o, m) and (j', o', m') are chosen from a solution x, and job j is shifted after the position of (j', o', m') as in neighborhood N_1. Notice that in this case, the triplets (j, o, m) and (j', o', m') are not necessarily part of the critical path. Then, the operation o_{jo} is assigned to another compatible machine which is randomly chosen.

4.3.2 Neighborhood structures for the local search

A local search consists of exploring all the neighbor solutions of a given solution x', and returning the best neighbor x'' according to an objective function. An objective function can maximize profits, minimize costs, minimize makespan, etc. In our case the objective function is the makespan, i.e., the minimization of the completion time of the last job. The defined neighborhood should not be too large, to avoid time overhead, and should contain enough good quality solutions to improve the incumbent solution found so far.

4.3.2.1 $\overline{N}_1$: Reassigning the machines in the critical path

The triplets are taken one by one, from the critical path of the incumbent solution x', going from left to right in the solution array. For each of the triplets (j, o, m), the corresponding operation o_{jo} is reassigned to the machine $m' \in M_{jo}$ that leads to the smallest makespan. If there is not a machine assignment that gives a better solution than the current one, the machine assignment remains the same. This process is applied to the next triplet on the critical path, and so on. A schematic representation of this procedure is illustrated in Figure 4.6.

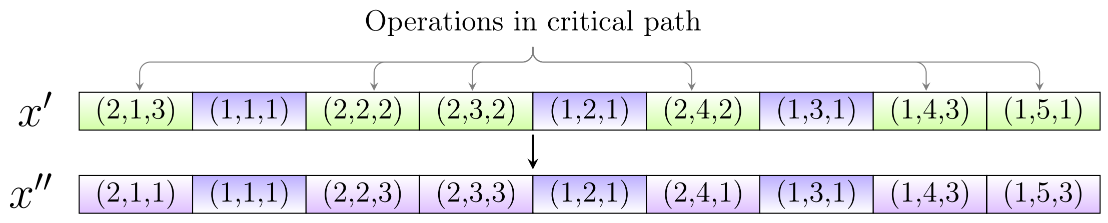


Figure 4.6: $\overline{N}_1$: Reassigning the machines in the critical path

4.3.2.2 $\overline{N}_2$: Reassigning the machines

This neighborhood is very similar to $\overline{N}_1$, but instead of performing the machine reassignment in the critical path, it is carried out on a subsequence of the incumbent solution x'. In order to reduce the size of the neighborhood, the number of operations of this subsequence is limited to 15% of the total number of operations. But in order to maintain a diversity of the neighborhoods, the first operation is randomly selected. The resultant feasible solution is named as x''.

4.3.2.3 $\overline{N}_3$: Swapping two jobs and reassigning the machines in a block

Two random triplets (j, o, m) and (j', o', m') are selected in a block of the solution x' and swapped as in N_2. Then, operations o_{jo} and $o_{j'o'}$ are reassigned to compatible machines by figuring out the machine that produces the smallest makespan. In this neighborhood, all possible swaps within the chosen block are explored.

4.3.2.4 $\overline{N}_4$: Shifting a job

A subsequence of operations from solution x' is randomly selected such that its length is approximately 15% of the total number of operations. Then the first operation of this subsequence is shifted to another position within this subsequence. All possible positions for the shifting are explored, while the machine assignment is preserved.

4.3.2.5 $\overline{N}_5$: Swapping two jobs

A subsequence of operations from solution x' is randomly selected such that its length is approximately 15% of the total number of operations. Then two triplets,

(j, o, m) and (j', o', m'), are selected, after that these triplets swap their positions to find out the best sequence that produces the minimum makespan, whilst conserving the machine assignment. All possible swaps are explored within this subsequence.

4.4 Computational Results

The proposed GVNS described in Algorithm 2 has been coded in C++, and the mathematical model has been used to solve the FRRC with the branch and bound available in CPLEX 12.6.3. All tests were carried out on a computer with a Processor 3.7 GHz Quad-Core Intel Xeon E5 with 12GB of RAM memory. For the tests, we used a set of benchmark instances adapted from the ones proposed by Dauzère-Pérès and Paulli [46] and Dauzére-Pérés and Paulli [47]. The resource requirement of operations was randomly chosen as well as the batch size of each resource. We made sure that at least two batches are available for the process. The recovery time was randomly selected between the minimum and the maximum processing time of the operations, to get consistent values according to the instance. As of stopping criterion for CPLEX, we considered one hour of computation time.

The characteristics of each class of the tested instances are presented in Table 4.1. Each row in this table is related to the instance class, in which ten different configurations of resources have been tested, the makespan and gap (%) are the averages of the ten instances. For instance, 'frrc5_08 'is a class of ten instances with the same number of operations and machines, but with different resource requirements configuration. The number '5' in the name indicates that five resources are used in the instance class. Moreover, the number of jobs, operations, machines, and the number of resources used in each class of the instance is shown explicitly in Table 4.1.

(a) instances with 1 resource

Instances	Number of -			
	jobs	operations	machines	resources
frrc1_01	10	196	5	1
frrc1_02	10	196	5	1
frrc1_03	10	196	5	1
frrc1_04	10	196	5	1
frrc1_05	10	196	5	1
frrc1_06	10	196	5	1
frrc1_07	15	293	8	1
frrc1_08	15	293	8	1
frrc1_09	15	293	8	1
frrc1_10	15	293	8	1
frrc1_11	15	293	8	1
frrc1_12	15	293	8	1
frrc1_13	20	387	10	1
frrc1_14	20	387	10	1
frrc1_15	20	387	10	1
frrc1_16	20	387	10	1
frrc1_17	20	387	10	1
frrc1_18	20	387	10	1

(b) instances with 5 resources

Instances	Number of -			
	jobs	operations	machines	resources
frrc5_01	10	196	5	5
frrc5_02	10	196	5	5
frrc5_03	10	196	5	5
frrc5_04	10	196	5	5
frrc5_05	10	196	5	5
frrc5_06	10	196	5	5
frrc5_07	15	293	8	5
frrc5_08	15	293	8	5
frrc5_09	15	293	8	5
frrc5_10	15	293	8	5
frrc5_11	15	293	8	5
frrc5_12	15	293	8	5
frrc5_13	20	387	10	5
frrc5_14	20	387	10	5
frrc5_15	20	387	10	5
frrc5_16	20	387	10	5
frrc5_17	20	387	10	5
frrc5_18	20	387	10	5

Table 4.1: Description of the tested instances

The mathematical model presented in section 3.3 has been implemented in C++, and solved with the branch and bound included in CPLEX. The results reported by CPLEX are presented in Table 4.2. Notice that in the cases where CPLEX did not report a feasible solution, within the one-hour time limit, the symbol '-' is used. For each class of the instances, we report the average makespan in the *makespan* column, the average optimality gap reported by CPLEX in column *gap*(%), and the number of instances where a feasible solution has been found out of the ten instances of the class in shown in the last column #*sol*. The averages have been computed taking into account only the instances where a feasible solution has been found. Note that, even for the smallest instances, CPLEX was not able to solve to optimality any of them and the optimality gap stays relatively high. For instances with more than 15 jobs, CPLEX struggles to find any feasible solution. The behavior with one or five resources is quite similar.

(a) with 1 resource

Instances	makespan	gap (%)	# sol
frrc1_01	10273.00	86.05	1/10
frrc1_02	10138.33	85.87	9/10
frrc1_03	10030.50	86.11	6/10
frrc1_04	10276.33	85.99	3/10
frrc1_05	9953.67	86.26	9/10
frrc1_06	10168.13	86.82	8/10
frrc1_07	-	-	0/10
frrc1_08	15133.20	90.75	5/10
frrc1_09	15085.44	90.72	9/10
frrc1_10	15124.00	90.66	2/10
frrc1_11	14983.40	91.08	5/10
frrc1_12	-	-	0/10
frrc1_13	-	-	0/10
frrc1_14	19967.60	93.22	10/10
frrc1_15	-	-	0/10
frrc1_16	-	-	0/10
frrc1_17	-	-	0/10
frrc1_18	-	-	0/10
Averages	12830.33	88.5	3.72/10

(b) with 5 resources

Instances	makespan	gap (%)	# sol
frrc5_01	-	-	0/10
frrc5_02	8270.43	83.04	7/10
frrc5_03	8858.67	84.16	9/10
frrc5_04	8589.50	83.15	8/10
frrc5_05	8889.89	84.57	9/10
frrc5_06	9218.80	85.45	5/10
frrc5_07	-	-	0/10
frrc5_08	13995.60	89.99	5/10
frrc5_09	14881.67	90.57	3/10
frrc5_10	-	-	0/10
frrc5_11	13666.33	90.21	3/10
frrc5_12	-	-	0/10
frrc5_13	-	-	0/10
frrc5_14	18725.63	92.77	8/10
frrc5_15	-	-	0/10
frrc5_16	-	-	0/10
frrc5_17	-	-	0/10
frrc5_18	-	-	0/10
Averages	11677.39	87.1	3.17/10

Table 4.2: CPLEX results using the proposed mathematical formulation

Table 4.3 shows the results obtained with the proposed GVNS, presented in Algorithm 2. Column *Instances* contains the name of the class, column *Ini sln* refers to the initial solution obtained with the constructive algorithm (Algorithm

3), and column *imp* shows the percentage of improvement between the best-found solution in column *makespan* and the initial solution *Ini sln*. The column *time* shows the average processing time in seconds. As one can see, the GVNS is able to improve the initial solution by around 9% and the processing time stays below 1500 s, in both the cases. Interestingly, the processing time is smaller with five resources; this is mainly due to an early convergence and then an early termination of the search.

(a) with 1 resource

Instances	Ini sln	makespan	imp	time
frrc1_01	3557.20	3175.40	10.67	79.22
frrc1_02	2834.40	2533.70	10.46	102.17
frrc1_03	2521.20	2354.70	6.56	166.46
frrc1_04	3328.10	2878.50	12.75	95.98
frrc1_05	2599.00	2374.40	8.27	127.13
frrc1_06	2770.20	2547.30	7.68	128.73
frrc1_07	3007.80	2662.50	11.38	412.31
frrc1_08	2521.90	2253.50	10.47	513.60
frrc1_09	2251.40	2180.80	3.12	392.71
frrc1_10	3057.40	2719.60	10.93	469.05
frrc1_11	2963.00	2670.70	9.23	300.29
frrc1_12	2374.80	2254.50	4.68	446.55
frrc1_13	3434.40	2885.40	15.34	1031.93
frrc1_14	2507.60	2370.20	5.43	949.06
frrc1_15	2388.50	2299.20	3.66	1484.57
frrc1_16	4382.00	3972.70	12.16	817.31
frrc1_17	3910.10	3722.20	6.24	893.03
frrc1_18	2978.60	2878.70	3.38	1337.27
Averages	2965.98	2707.44	8.47	541.52

(b) with 5 resources

Instances	Ini sln	makespan	imp	time
frrc5_01	3420.20	2974.40	12.89	76.63
frrc5_02	2960.20	2547.40	13.44	80.27
frrc5_03	2722.40	2520.50	7.05	60.99
frrc5_04	3388.20	2860.90	15.33	69.22
frrc5_05	2702.20	2467.20	8.41	55.85
frrc5_06	2519.40	2397.70	4.80	80.94
frrc5_07	3908.50	3183.70	17.25	234.98
frrc5_08	2755.20	2487.50	8.47	164.74
frrc5_09	2893.10	2702.30	5.12	155.20
frrc5_10	3353.20	2869.50	13.88	326.79
frrc5_11	3096.20	2754.10	10.09	174.13
frrc5_12	2396.10	2278.30	4.31	184.44
frrc5_13	3218.80	2850.00	11.32	678.35
frrc5_14	2960.30	2817.40	4.56	369.73
frrc5_15	3489.20	3408.10	2.03	327.83
frrc5_16	3777.80	3219.20	14.16	706.10
frrc5_17	2800.30	2610.40	5.63	417.00
frrc5_18	2773.90	2664.50	3.16	525.69
Averages	3063.07	2756.28	9.00	260.49

Table 4.3: GVNS results

When many resources are introduced, we have more flexibility in the arrangement of the operations and less total waiting time for the availability of the resources. With only one resource, it is more likely that we generate large dead time in the process during the resource recovery period which leads to a more complex scheduling. Alternating operations using different resources is not an option in this case. However, the improvement of the initial solution stays relatively consistent with one and five resources. If we compare the results reported by CPLEX and the GVNS, we can remark that the average makespan of the GVNS is much smaller than the one reported by CPLEX. The difference is around 75% and the processing time of the GVNS stays relatively low.

Chapter 5

Case study - Scheduling problem in a brewery

In this chapter, we present a case study from a local brewing company. The objective is to propose a complete beer production schedule in order to minimize the makespan. It can be seen as a multi-stage batch scheduling problem where each stage involves multiple parallel machines and sequence-dependent setup times. The jobs are grouped in families of products according to the kind of beer to be produced and the capacity of the different tanks used during the process should not be exceeded. Besides the tanks, another renewable resource to be considered is the yeast, required for the fermentation process of beer.

To the best of our knowledge, this problem has not been previously addressed in the literature. We propose a Greedy Randomize Adaptive Search Procedure (GRASP) for its solution. The contents of this chapter have been published in: *Sáenz-Alanís, César A., V. D. Jobish, M. Angélica Salazar-Aguilar, and Vincent Boyer. "A parallel machine batch scheduling problem in a brewing company". The International Journal of Advanced Manufacturing Technology 87, no. 1-4 (2016): 65-75.*

5.1 PROBLEM DESCRIPTION - THE BREWING PROBLEM

In the beer brewing process, beers are obtained from the production of worts, which contain the sugars that will be fermented to produce alcohol. The peculiarities of a beer depend on the malt used to produce the wort and on the yeast. Since different kinds of beers can be obtained by a brewery, the production of different kind of worts has to be scheduled. Furthermore, the process is constrained by the cleaning operation of the tanks, the availability of the tanks, the time required to empty a tank, and the availability of the yeasts. The process consists of three main phases: the coction, the fermentation, and the conditioning. In this work we consider only the two first phases since, as observed in our case study, there are always enough tanks in the conditioning phase to receive the worts leaving the fermentation tanks.

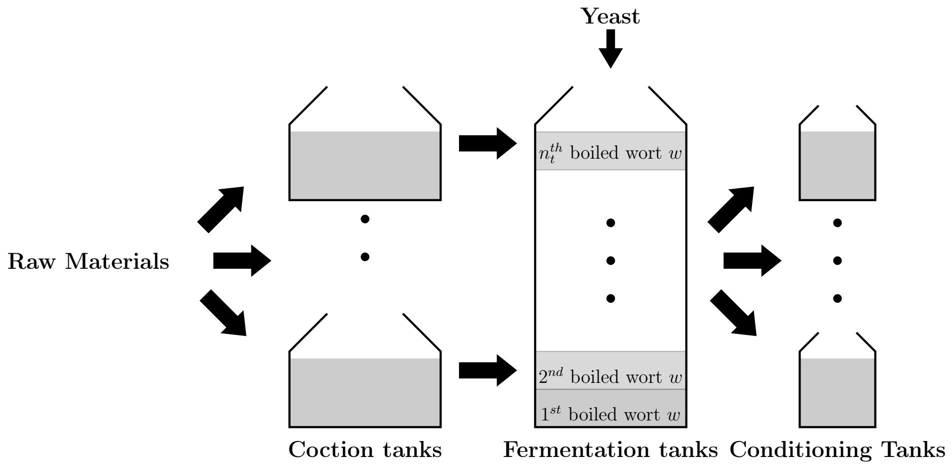


Figure 5.1: General Brewing Process

Let W be the set of wort types and d_w the demand of each wort type $w \in W$, then the objective is to schedule the coction and the fermentation of the worts in order to satisfy the demand as soon as possible. Coctions can be carried out on a set H of coction houses, which is composed of tanks with capacity q_h, $h \in H$. The coction houses can operate in parallel and are unrelated. For each wort type $w \in W$, there is a subset of compatible coction houses $H_w \in H$. In the fermentation phase, there is a set T of heterogeneous tanks available. Each tank $t \in T$ has a capacity k_t

which represents the number of worts needed to fill the tank t.

In this context, we model a job as a batch of alike worts. The number of worts on this batch is equal to the capacity q_h of the fermentation tank h used for the second phase. Hence, the batch size for each job is unknown a priori and, consequently, the total number of jobs to be scheduled either. Although, the fermentation of a batch occurs in a unique tank, the coction of worts within a batch can be done in parallel on the different coction houses. Nevertheless, one has to assure that the assigned fermentation tank is available when the first wort of the batch leaves the coction house, and only the wort from the associated batch can fill this fermentation tank.

The availability of the yeast should also be considered. Let Y be the set of yeasts for the fermentation phase and n_y the maximum number of consecutive jobs that can use yeast $y \in Y$ before it is depleted. Each wort $w \in W$ can be fermented by using a specific yeast $y_w \in Y$. Hence, a yeast $y \in Y$ is used for a subset $F_y \subset W$ of wort type. F_y will be called the family of worts type that are compatible with yeast y. In order to assure the availability of yeast, the production of worts using a different kind of yeast is alternated. Indeed, this policy is used by the company in order to ensure yeast recovery. Besides, as we will see in the following, this strategy is particularly relevant when considering the maintenance activities.

Maintenance activities occur at each stage of the process. The coction tanks should be cleaned every time there is a changed in the wort type, and also after n consecutive coctions of the same wort type. Likewise, the fermentation tanks should be cleaned after each use. The duration of these cleaning operations depends on the wort yielding to Sequence Dependent Setup Time. Moreover, a general maintenance of the production lines should be scheduled every 7 to 10 days.

5.2 Solution procedure for the brewing problem

For the solution of this NP-hard scheduling problem, we propose a Greedy Randomized Adaptive Search Procedure (GRASP). GRASP is a multi-start process, where each iteration consists of a construction phase and an improvement phase. The construction phase constructs a solution for the problem, then this solution is improved through the improvement phase, which is a local search procedure. The general steps of the GRASP algorithm is presented in Algorithm 4, where S^b is the best-found solution.

Algorithm 4 GRASP algorithm

```
Input:
    Instance of the problem
    $it_{max}$: Maximum number of iterations for the GRASP
Output: $S^b$ Best found solution.
 1: $j \leftarrow 0$
 2: $S^b \leftarrow \emptyset$
 3: while $j < it_{max}$ do
 4:     $S \leftarrow$ construct_solution()
 5:     $S' \leftarrow$ improve_solution($S$)
 6:     Update $S$
 7:     Update $S^b$
 8:     $j \leftarrow j + 1$
 9: end while
10: return $S^b$
```

5.2.1 Construction phase

This phase consists of constructing an initial solution which will be fed to the improvement phase. At each step of the algorithm, an empty batch B is created and the wort type to be produced in B is randomly selected from a Restricted Candidate List (RCL). The RCL contains the two types of worts, one that has the largest uncovered demand and the one whose required yeast is available at the moment. The batch B is assigned to the first available fermentation tank $t^* \in T$, which gives the number n_B of coctions that should be programmed. The required coctions are then assigned iteratively to the earliest available coction house. The procedure is repeated until the demand of all the wort types is satisfied. This constructive procedure is given in Algorithm 5.

Algorithm 5 Constructive algorithm

```
Input:
    Data of the problem
Output:  $S^b$ Best found solution.
1: $S \leftarrow \emptyset$
2: while Meet stopping criteria do
3:     Build RCL of wort batches $B$
4:     Select a random batch $B$ from RCL
5:     Update $(S, S^b)$
6:     Evaluate stopping criteria
7: end while
8: return $S^b$
```

5.2.2 Improvement phase

The improvement phase tries to improve the constructed solution S. This procedure works in an iterative fashion by successively replacing the current solution S^* by the best solution S' in its neighborhood. It finishes when no better solution has been found. The neighborhood of the current solution is obtained by randomly swapping two batches of different wort type and recomputing the makespan. If a better solution is found, it becomes the new current solution, and its neighborhood is afterward explored, and so on. An outline of this procedure is presented in Algorithm 6.

Algorithm 6 Solution Improvement

```
Input:
    Data of the problem
    S : Initial solution
Output: $S^*$ Best found solution.
1: $S^* \leftarrow S$
2: while Meet stopping criteria do
3:     Find $S' \in N(S^*)$, such that makespan of $S'$ is better than $S^*$
4:     Update $S^*$
5: end while
6: return $S^*$
```

5.3 Experimental results

The computational experiments are carried out with real instances from a brewery and we also generated some random instances to evaluate the efficiency and robustness of the proposed GRASP. The GRASP Algorithm has been implemented in Java and tested on a Workstation HP Z620 with an Intel Xeon(R) CPU E5-2620 v2 (2.10 GHz) and 64GB of RAM memory. The main characteristics of these instances are,

- Two coction houses with different setup times
- Two sizes of fermentation tanks that can contain 4 or 8 units of worts
- Two kinds of yeasts

* At most three consecutive uses of each kind of yeast

* Six different wort types

For the real data, the brewery provided the demand per wort type on 20 cases from the year 2014. The comparison between the makespan (number of days required to carry out the production) obtained by GRASP and the one from the solutions implemented by the company are shown in Figure 5.2. It is clear that the GRASP outperforms the solution used by the decision maker over all tested instances.

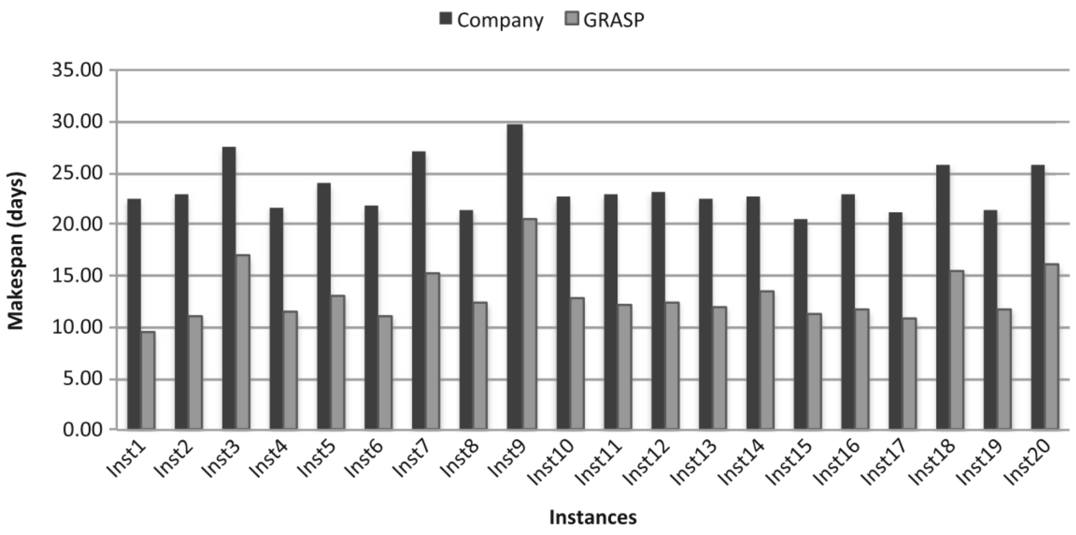


Figure 5.2: Makespan comparison with real data: company solution vs GRASP

Table 5.1 presents a comparative study on the values reported by our GRASP and the one of the decision maker at the brewery. The number of days required for production is significantly reduced when GRASP is used. An average of 44.80% of the total number of production days needed by the company is saved. This result has a direct impact on the production capacity of the plant and the tolerance to faults that can occur throughout the process. Furthermore, the computation time required by the proposed GRASP is less than 11 seconds in average, while the decision maker has to work during a whole working day to obtain a feasible sequence of production per instance.

	Company (days)	GRASP (days)	Time (s)	Gap (%)
Min	20.44	9.46	7.08	31.02
Avg	23.51	13.07	10.70	44.80
Max	29.78	20.54	15.49	57.90

Table 5.1: Computational Experiments with Real Data

The production demand in the brewery varies throughout the year: a low level of production during winter, a high level of production during summer, and a normal level of production in the rest of the year. Thus, to test the robustness of our heuristic, from the real data, we have generated three classes of instances with low, medium, and high demand.

For each class, we generated 20 instances, and we report the total number of days (makespan) required to fulfill the demand and the processing time used by the proposed GRASP. The results obtained are displayed in Table 5.2.

Demand -		Average
deviation	GRASP(days)	time(seconds)
Low	14.74	9.83
Medium	15.72	13.42
High	16.98	16.39

Table 5.2: Average results of instances with varying demands

From Table 5.2, one can notice that the proposed GRASP takes less than 19 seconds in average to provide a solution for those artificial instances. Furthermore, the processing time is consistent over all tested instances and in the worst case the number of days (makespan) required to fulfill the demand stays below 18 days while the company usually takes more than 20 days in the best case. These results show that a brewing company can highly benefit from such an approach when it needs to schedule its production.

5.4 Conclusions

In this chapter, we have presented a scheduling problem found in a brewing company. Due to the complex nature of the problem, we propose a computational procedure based on the metaheuristic known as GRASP. The main characteristics of the problem are the existence of parallel machines, two stages of production, multiple products, batch production, and sequence-dependent setup times. Moreover, the batches have different sizes and their total number depends on the production schedule. The experimental tests over the real instances from the brewing company and over artificial instances show the high efficiency and the robustness of our approach. Indeed, our GRASP can generate a feasible sequence of production in a significantly negligible time in comparison to the current time required by the decision maker at the company. Furthermore, with the instances provided by the brewery, the solution obtained by GRASP saves a significant amount of time in production, which gives the opportunity to the company to increase its capacity of production without inverting in new equipments. The proposed approach can also be used to evaluate the need of a future expansion of capacity in the plant.

Chapter 6

Conclusions

6.1 Contributions and Future Work

In this study, we introduce a new problem called the Flexible job-shop scheduling problem with Resource Recovery Constraints, i.e., FRRC. The primary characteristics of the FRRC are the renewable resources (which are available by batches), resource recovery time, and operation-resource compatibility. Some other features are the existence of multiple jobs composed of operations, multiple machines available in parallel, precedence constraints, operation-machine compatibility, and processing time dependent of the machine and operation. Several researchers have studied problems with some of these characteristics and proposed a variety of solution procedures and mathematical model representations towards these problems. But, to the best of our knowledge, none of the researchers have worked on a scheduling problem that tackles these features simultaneously.

A mixed integer linear formulation to represent the FRRC and a solution procedure based on a General Variable Neighborhood Search metaheuristic have been proposed. Computational tests have been carried out in a large set of instances adapted from the literature of the FJSP. The results clearly showed the efficiency of our proposed algorithm (see Chapter 4). Moreover, the manuscript derived from this part of the research has been submitted for revision to The International Journal of Production Research.

Additionally, a case study from a local brewery has been carried out (see Chapter 5). A solution procedure based on GRASP has been proposed. The efficiency of the algorithm has been shown by solving real and random instances. The description of the algorithm as well as the obtained results are already published in: *Sáenz-Alanís, César A., V. D. Jobish, M. Angélica Salazar-Aguilar, and Vincent Boyer. "A parallel machine batch scheduling problem in a brewing company". The International Journal of Advanced Manufacturing Technology 87, no. 1-4 (2016): 65-75.*

Notice that, the complex nature of the modern industries often involved many resources in their process, with limited production units and pieces of machinery. But the production must have to finish in a short time without loss in quality. In this context, a well-planned production is essential. On behalf of this research, we note that manual scheduling is very time consuming, and the outputs are not very efficient in practice. Besides, even linear mathematical models have limitations to provide optimum or near optimum solutions in a reasonably short period. Solution procedures based on GVNS or GRASP are light and easy to implement heuristics that could save time, money and improve significantly the production capacity of the companies.

In a future work, other solution approaches for the FRRC should be investigated in order to state the quality of the solutions obtained with the proposed GVNS. Besides, the mathematical model can be studied and improved in order to obtain feasible solutions for at least some instances. It could be also interesting to extend the problem where each operation uses more than one resource, with different availability profiles in order to tackle more complex industrial problems. Regarding the case study, the implementation in the company of the proposed GRASP would be an interesting task. Furthermore, one can also consider adding the conditioning phase and the bottling phase in order to optimize the overall production process.

6.1 Autobiographical reflection

Undertaking this research is an invaluable learning experience in my academic life and career. Before starting this research, I did not have much idea on how the products in a supermarket or available to order online are processed. Now I realize that behind each product there is an immense study on the gathering of raw materials, the configuration of the production lines, the conditioning of the product, and even their distribution. At each stage of production and distribution behind each product, a high attention of the decision maker is required in order to fulfill the demand.

More than anything else, I have gained an in-depth understanding of the nature of the research, that it can be cyclical, sometimes messy or even failed. I have learned how to gather information, to define and model a problem, to review the literature, to develop heuristic solution procedures and to evaluate them. All together gave me a life long experience in both my academic and personal life.

Bibliography

[1] Akkan, C., Drexl, A., and Kimms, A. (2005). Network decomposition-based benchmark results for the discrete time–cost tradeoff problem. *European Journal of Operational Research*, 165(2):339–358.

[2] Alcaraz, J., Maroto, C., and Ruiz, R. (2003). Solving the multi-mode resource-constrained project scheduling problem with genetic algorithms. *Journal of the Operational Research Society*, 54(6):614–626.

[3] Allahverdi, A., Ng, C., Cheng, T. E., and Kovalyov, M. Y. (2008). A survey of scheduling problems with setup times or costs. *European Journal of Operational Research*, 187(3):985–1032.

[4] Almeida, B. F., Correia, I., and Saldanha-da Gama, F. (2016). Priority-based heuristics for the multi-skill resource constrained project scheduling problem. *Expert Systems with Applications*, 57:91–103.

[5] Alvarez-Valdes, R., Crespo, E., Tamarit, J. M., and Villa, F. (2006). A scatter search algorithm for project scheduling under partially renewable resources. *Journal of Heuristics*, 12(1):95–113.

[6] Alvarez-Valdés, R., Crespo, E., Tamarit, J. M., and Villa, F. (2008). Grasp and path relinking for project scheduling under partially renewable resources. *European Journal of Operational Research*, 189(3):1153–1170.

[7] Artigues, C., Demassey, S., and Neron, E. (2013). *Resource-constrained project scheduling: models, algorithms, extensions and applications*. John Wiley & Sons.

[8] Azzouz, A., Ennigrou, M., and Said, L. B. (2016). Flexible job-shop scheduling problem with sequence-dependent setup times using genetic algorithm. In *Proceedings of the 18th International Conference on Enterprise Information Systems (ICEIS 2016)*, volume 2, pages 47–53. Science and Technology Publications.

[9] Ba, L., Li, Y., Yang, M., Gao, X., and Liu, Y. (2016). Modeling and simulation of a multi-resource flexible job-shop scheduling. *International Journal of Simulation Modelling (IJSIMM)*, 15(1).

[10] Bagheri, A. and Zandieh, M. (2011). Bi-criteria flexible job-shop scheduling with sequence-dependent setup times-variable neighborhood search approach. *Journal of Manufacturing Systems*, 30(1):8–15.

[11] Beşikci, U., Bilge, Ü., and Ulusoy, G. (2015). Multi-mode resource constrained multi-project scheduling and resource portfolio problem. *European Journal of Operational Research*, 240(1):22–31.

[12] Bianco, L. and Caramia, M. (2013). A new formulation for the project scheduling problem under limited resources. *Flexible Services and Manufacturing Journal*, 25(1-2):6–24.

[13] Bianco, L., Dell'Olmo, P., and Speranza, M. G. (1998). Heuristics for multimode scheduling problems with dedicated resources. *European Journal of Operational Research*, 107(2):260–271.

[14] Birewar, D. B. and Grossmann, I. E. (1990). Simultaneous production planning and scheduling in multiproduct batch plants. *Industrial & engineering chemistry research*, 29(4):570–580.

[15] Boctor, F. F. (1996). A new and efficient heuristic for scheduling projects with resource restrictions and multiple execution modes. *European Journal of Operational Research*, 90(2):349–361.

[16] Böttcher, J., Drexl, A., Kolisch, R., and Salewski, F. (1999). Project scheduling

under partially renewable resource constraints. *Management Science*, 45(4):543–559.

[17] Bouleimen, K. and Lecocq, H. (2003). A new efficient simulated annealing algorithm for the resource-constrained project scheduling problem and its multiple mode version. *European Journal of Operational Research*, 149(2):268–281.

[18] Bożejko, W., Uchroński, M., and Wodecki, M. (2010). Parallel hybrid metaheuristics for the flexible job shop problem. *Computers & Industrial Engineering*, 59(2):323–333.

[19] Brandimarte, P. (1993). Routing and scheduling in a flexible job shop by tabu search. *Annals of Operations research*, 41(3):157–183.

[20] Brucker, P., Drexl, A., Möhring, R., Neumann, K., and Pesch, E. (1999). Resource-constrained project scheduling: Notation, classification, models, and methods. *European journal of operational research*, 112(1):3–41.

[21] Brucker, P. and Knust, S. (2012). *Complex Scheduling (GOR-Publications)*. Springer.

[22] Brucker, P., Knust, S., Schoo, A., and Thiele, O. (1998a). A branch and bound algorithm for the resource-constrained project scheduling problem. *European Journal of Operational Research*, 107(2):272–288.

[23] Brucker, P., Kovalyov, M. Y., Shafransky, Y. M., and Werner, F. (1998b). Batch scheduling with deadlines on parallel machines. *Annals of Operations Research*, 83:23–40.

[24] Brucker, P. and Schlie, R. (1990). Job-shop scheduling with multi-purpose machines. *Computing*, 45(4):369–375.

[25] Buddhakulsomsiri, J. and Kim, D. S. (2006). Properties of multi-mode resource-constrained project scheduling problems with resource vacations and activity splitting. *European Journal of Operational Research*, 175(1):279–295.

[26] Buddhakulsomsiri, J. and Kim, D. S. (2007). Priority rule-based heuristic for multi-mode resource-constrained project scheduling problems with resource vacations and activity splitting. *European Journal of Operational Research*, 178(2):374–390.

[27] Buscher, U. and Shen, L. (2009). Solving the batch scheduling problem with family setup times. In *Operations Research Proceedings 2008*, pages 117–122. Springer.

[28] Buscher, U. and Shen, L. (2010). Mip formulations and heuristics for solving parallel batching problems. *Journal of Systems Science and Complexity*, 23(5):884–895.

[29] Chakrabortty, R. K., Sarker, R. A., and Essam, D. L. (2016). Multi-mode resource constrained project scheduling under resource disruptions. *Computers & Chemical Engineering*, 88:13–29.

[30] Chan, F., Wong, T., and Chan, L. (2006). Flexible job-shop scheduling problem under resource constraints. *International Journal of Production Research*, 44(11):2071–2089.

[31] Chang, P.-Y., Damodaran, P., and Melouk, S. (2004). Minimizing makespan on parallel batch processing machines. *International Journal of Production Research*, 42(19):4211–4220.

[32] Chaudhry, I. A. and Khan, A. A. (2016). A research survey: review of flexible job shop scheduling techniques. *International Transactions in Operational Research*, 23(3):551–591.

[33] Chen, Z.-J. and Chyu, C.-C. (2012). Solving the resource constrained project scheduling problem to minimize the financial failure risk. *International Journal of Advanced Research in Artificial Intelligence*, 1(1).

[34] Cheng, B., Wang, Q., Yang, S., and Hu, X. (2013). An improved ant colony

optimization for scheduling identical parallel batching machines with arbitrary job sizes. *Applied Soft Computing*, 13(2):765–772.

[35] Cheng, J., Fowler, J., Kempf, K., and Mason, S. (2015). Multi-mode resource-constrained project scheduling problems with non-preemptive activity splitting. *Computers & Operations Research*, 53:275–287.

[36] Cheng, T. and Chen, Z.-L. (1994). Parallel machine scheduling with batch setup times. *Operations Research*, 42(6):1171–1174.

[37] Cheng, T. E., Lin, B. M., and Huang, H. (2012). Resource-constrained flowshop scheduling with separate resource recycling operations. *Computers & Operations Research*, 39(6):1206–1212.

[38] Chung, S., Tai, Y., and Pearn, W. (2009). Minimising makespan on parallel batch processing machines with non-identical ready time and arbitrary job sizes. *International Journal of Production Research*, 47(18):5109–5128.

[39] Chyu, C.-C. and Chen, Z.-J. (2009). Scheduling jobs under constant period-by-period resource availability to maximize project profit at a due date. *The International Journal of Advanced Manufacturing Technology*, 42(5-6):569–580.

[40] Colak, S., Agarwal, A., and Erenguc, S. (2013). Multi-mode resource-constrained project-scheduling problem with renewable resources: new solution approaches. *Journal of Business & Economics Research (Online)*, 11(11):455.

[41] Condotta, A., Knust, S., and Shakhlevich, N. V. (2010). Parallel batch scheduling of equal-length jobs with release and due dates. *Journal of Scheduling*, 13(5):463–477.

[42] Costa, A. (2015). Hybrid genetic optimization for solving the batch-scheduling problem in a pharmaceutical industry. *Computers & Industrial Engineering*, 79:130–147.

[43] Crauwels, H., Beullens, P., and Van Oudheusden, D. (2006). Parallel machine scheduling by family batching with sequence-independent set-up times. *International Journal of Operations Research*, 3(2):144–154.

[44] Damodaran, P., Ghrayeb, O., and Guttikonda, M. C. (2013). Grasp to minimize makespan for a capacitated batch-processing machine. *The International Journal of Advanced Manufacturing Technology*, 68(1-4):407–414.

[45] Dastidar, S. G. and Nagi, R. (2007). Batch splitting in an assembly scheduling environment. *International Journal of Production Economics*, 105(2):372–384.

[46] Dauzère-Pérès, S. and Paulli, J. (1995). Solving the general multiprocessor job-shop scheduling problem. *Working Papers, Department of Mathematical Sciences, University of Aarhus.*

[47] Dauzére-Pérés, S. and Paulli, J. (1997). An integrated approach for modeling and solving the general multiprocessor job-shop scheduling problem using tabu search. *Annals of Operations Research*, 70:281–306.

[48] Dauzère-Pérès, S., Roux, W., and Lasserre, J. (1998). Multi-resource shop scheduling with resource flexibility. *European Journal of Operational Research*, 107(2):289–305.

[49] Davis, E. W. and Heidorn, G. E. (1971). An algorithm for optimal project scheduling under multiple resource constraints. *Management Science*, 17(12):B–803.

[50] De Reyck, B. and Herroelen, W. (1999). The multi-mode resource-constrained project scheduling problem with generalized precedence relations. *European Journal of Operational Research*, 119(2):538–556.

[51] Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). A fast and elitist multi-objective genetic algorithm: Nsga-ii. *IEEE transactions on evolutionary computation*, 6(2):182–197.

[52] Defersha, F. M. and Chen, M. (2010). A parallel genetic algorithm for a flexible job-shop scheduling problem with sequence dependent setups. *The international journal of advanced manufacturing technology*, 49(1-4):263–279.

[53] Demeulemeester, E., De Reyck, B., Foubert, B., Herroelen, W., and Vanhoucke, M. (1998). New computational results on the discrete time/cost trade-off problem in project networks. *Journal of the Operational Research Society*, 49(11):1153–1163.

[54] Demeulemeester, E. and Herroelen, W. (1992). A branch-and-bound procedure for the multiple resource-constrained project scheduling problem. *Management science*, 38(12):1803–1818.

[55] Demir, Y. and İşleyen, S. K. (2013). Evaluation of mathematical models for flexible job-shop scheduling problems. *Applied Mathematical Modeling*, 37(3):977–988.

[56] Dorsey, R. C., Hodgson, T. J., and Ratliff, H. D. (1974). Technical note-a production-scheduling problem with batch processing. *Operations Research*, 22(6):1271–1279.

[57] Drexl, A. and Kimms, A. (1997). Lot sizing and scheduling - survey and extensions. *European Journal of operational research*, 99(2):221–235.

[58] Drexl, A., Nissen, R., Patterson, J. H., and Salewski, F. (2000). Progen/πx–an instance generator for resource-constrained project scheduling problems with partially renewable resources and further extensions. *European Journal of Operational Research*, 125(1):59–72.

[59] ElMaraghy, H., Patel, V., and Abdallah, I. B. (2000). Scheduling of manufacturing systems under dual-resource constraints using genetic algorithms. *Journal of Manufacturing Systems*, 19(3):186–201.

[60] Fattahi, P., Mehrabad, M. S., and Jolai, F. (2007). Mathematical modeling

and heuristic approaches to flexible job-shop scheduling problems. *Journal of Intelligent Manufacturing*, 18(3):331–342.

[61] Figielska, E. (2006). Combining an optimizing method with a genetic algorithm to solve a flowshop scheduling problem with additional resources. In *2006 IEEE Conference on Emerging Technologies and Factory Automation*, pages 1080–1086. IEEE.

[62] Figielska, E. (2008). A new heuristic for scheduling the two-stage flowshop with additional resources. *Computers & Industrial Engineering*, 54(4):750–763.

[63] Figielska, E. (2009). A genetic algorithm and a simulated annealing algorithm combined with column generation technique for solving the problem of scheduling in the hybrid flowshop with additional resources. *Computers & Industrial Engineering*, 56(1):142–151.

[64] Figielska, E. (2010). Heuristic algorithms for preemptive scheduling in a two-stage hybrid flowshop with additional renewable resources at each stage. *Computers & Industrial Engineering*, 59(4):509–519.

[65] Gambardella, L. and Mastrolilli, M. (1996). Effective neighborhood functions for the flexible job shop problem. *Journal of Scheduling*, 3(3).

[66] Gao, J., Sun, L., and Gen, M. (2008). A hybrid genetic and variable neighborhood descent algorithm for flexible job shop scheduling problems. *Computers & Operations Research*, 35(9):2892–2907.

[67] Gao, L. and Pan, Q.-K. (2016). A shuffled multi-swarm micro-migrating birds optimizer for a multi-resource-constrained flexible job shop scheduling problem. *Information Sciences*, 372:655–676.

[68] Garey, M. R., Johnson, D. S., and Sethi, R. (1976). The complexity of flowshop and job-shop scheduling. *Mathematics of operations research*, 1(2):117–129.

[69] Gargeya, V. B. and Deane, R. (1996). Scheduling research in multiple resource constrained job shops: a review and critique. *International Journal of Production Research*, 34(8):2077–2097.

[70] Ghosh, J. B. (1994). Batch scheduling to minimize total completion time. *Operations Research Letters*, 16(5):271–275.

[71] Graham, R. L., Lawler, E. L., Lenstra, J. K., and Kan, A. R. (1979). Optimization and approximation in deterministic sequencing and scheduling: a survey. *Annals of discrete mathematics*, 5:287–326.

[72] Graves, S. C. (1981). A review of production scheduling. *Operations Research*, 29(4):646–675.

[73] Hall, N. G. and Potts, C. N. (2005). The coordination of scheduling and batch deliveries. *Annals of operations research*, 135(1):41–64.

[74] Hall, N. G. and Sriskandarajah, C. (1996). A survey of machine scheduling problems with blocking and no-wait in process. *Operations research*, 44(3):510–525.

[75] Hartmann, S. (2001). Project scheduling with multiple modes: a genetic algorithm. *Annals of Operations Research*, 102(1-4):111–135.

[76] Hartmann, S. and Briskorn, D. (2010). A survey of variants and extensions of the resource-constrained project scheduling problem. *European Journal of operational research*, 207(1):1–14.

[77] Hartmann, S. and Drexl, A. (1998). Project scheduling with multiple modes: A comparison of exact algorithms. *Networks*, 32(4):283–297.

[78] Heilmann, R. (2001). Resource–constrained project scheduling: a heuristic for the multi–mode case. *OR-Spektrum*, 23(3):335–357.

[79] Heilmann, R. (2003). A branch-and-bound procedure for the multi-mode resource-constrained project scheduling problem with minimum and maximum time lags. *European Journal of Operational Research*, 144(2):348–365.

[80] Hermel, D., Hasheminia, H., Adler, N., and Fry, M. J. (2016). A solution framework for the multi-mode resource-constrained cross-dock scheduling problem. *Omega*, 59:157–170.

[81] Huang, H.-H., Huang, C.-H., and Pei, W. (2015). Solving multi-resource constrained project scheduling problem using ant colony optimization. *Journal of Engineering, Project, and Production Management*, 5(1):2.

[82] Huang, S., Tian, N., and Ji, Z. (2016). Particle swarm optimization with variable neighborhood search for multi-objective flexible job shop scheduling problem. *International Journal of Modeling, Simulation, and Scientific Computing*, page 1650024.

[83] Hurink, J., Jurisch, B., and Thole, M. (1994). Tabu search for the job-shop scheduling problem with multi-purpose machines. *Operations-Research-Spektrum*, 15(4):205–215.

[84] Jaber, M. and Neumann, W. (2010). Modelling worker fatigue and recovery in dual-resource constrained systems. *Computers & Industrial Engineering*, 59(1):75–84.

[85] Jarboui, B., Damak, N., Siarry, P., and Rebai, A. (2008). A combinatorial particle swarm optimization for solving multi-mode resource-constrained project scheduling problems. *Applied Mathematics and Computation*, 195(1):299–308.

[86] Jia, Z.-h. and Leung, J. Y.-T. (2015). A meta-heuristic to minimize makespan for parallel batch machines with arbitrary job sizes. *European Journal of Operational Research*, 240(3):649–665.

[87] Józefowska, J., Mika, M., Różycki, R., Waligóra, G., and Węglarz, J. (2001).

Simulated annealing for multi-mode resource-constrained project scheduling. *Annals of Operations Research*, 102(1-4):137–155.

[88] Karthikeyan, S., Asokan, P., and Nickolas, S. (2014). A hybrid discrete firefly algorithm for multi-objective flexible job shop scheduling problem with limited resource constraints. *The International Journal of Advanced Manufacturing Technology*, 72(9-12):1567–1579.

[89] Kashan, A. H., Karimi, B., and Jenabi, M. (2008). A hybrid genetic heuristic for scheduling parallel batch processing machines with arbitrary job sizes. *Computers & Operations Research*, 35(4):1084–1098.

[90] Kim, J., Kang, S.-H., and Lee, S.-M. (1997). Transfer batch scheduling for a two-stage flowshop with identical parallel machines at each stage. *Omega*, 25(5):547–555.

[91] Klein, R. (2000). Project scheduling with time-varying resource constraints. *International Journal of Production Research*, 38(16):3937–3952.

[92] Klemmt, A., Weigert, G., Almeder, C., and Monch, L. (2009). A comparison of mip-based decomposition techniques and vns approaches for batch scheduling problems. In *Simulation Conference (WSC), Proceedings of the 2009 Winter*, pages 1686–1694. IEEE.

[93] Kolisch, R. (1996). Serial and parallel resource-constrained project scheduling methods revisited: Theory and computation. *European Journal of Operational Research*, 90(2):320–333.

[94] Kolisch, R. and Drexl, A. (1997). Local search for nonpreemptive multi-mode resource-constrained project scheduling. *IIE transactions*, 29(11):987–999.

[95] Kolisch, R., Sprecher, A., and Drexl, A. (1995). Characterization and generation of a general class of resource-constrained project scheduling problems. *Management science*, 41(10):1693–1703.

[96] Lang, M. and Li, H. (2011). Research on dual-resource multi-objective flexible job shop scheduling under uncertainty. In *Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC), 2011 2nd International Conference on*, pages 1375–1378. IEEE.

[97] Lei, D. and Guo, X. (2014). Variable neighbourhood search for dual-resource constrained flexible job shop scheduling. *International Journal of Production Research*, 52(9):2519–2529.

[98] Lei, D. and Tan, X. (2016). Local search with controlled deterioration for multi-objective scheduling in dual-resource constrained flexible job shop. In *2016 Chinese Control and Decision Conference (CCDC)*, pages 4921–4926. IEEE.

[99] Leung, J. Y.-T., Ng, C., and Cheng, T. E. (2008). Minimizing sum of completion times for batch scheduling of jobs with deteriorating processing times. *European Journal of Operational Research*, 187(3):1090–1099.

[100] Li, J. and Huang, Y. (2015). Improved genetic algorithm for extension dual resource constrained job shop scheduling problem. In *LISS 2014*, pages 1105–1110. Springer.

[101] Li, J. and Huang, Y. (2016). A hybrid genetic algorithm for dual-resource constrained job shop scheduling problem. In *International Conference on Intelligent Computing*, pages 463–475. Springer.

[102] Li, J., Huang, Y., and Niu, X. (2016). A branch population genetic algorithm for dual-resource constrained job shop scheduling problem. *Computers & Industrial Engineering*, 102:113–131.

[103] Li, J., Pan, Q.-k., and Xie, S. (2010a). A hybrid variable neighborhood search algorithm for solving multi-objective flexible job shop problems. *Comput. Sci. Inf. Syst.*, 7(4):907–930.

[104] Li, J.-q., Pan, Q., Xie, S., Jia, B.-x., and Wang, Y.-t. (2010b). A hybrid particle swarm optimization and tabu search algorithm for flexible job-shop scheduling

problem. *International Journal of Computer Theory and Engineering*, 2(2):1793–8201.

[105] Li, J.-q., Pan, Q.-k., and Liang, Y.-C. (2010c). An effective hybrid tabu search algorithm for multi-objective flexible job-shop scheduling problems. *Computers & Industrial Engineering*, 59(4):647–662.

[106] Li, K., Yang, S.-L., and Ma, H.-W. (2011). A simulated annealing approach to minimize the maximum lateness on uniform parallel machines. *Mathematical and Computer Modeling*, 53(5):854–860.

[107] Li, S. and Yuan, J. (2010). Parallel-machine parallel-batching scheduling with family jobs and release dates to minimize makespan. *Journal of Combinatorial Optimization*, 19(1):84–93.

[108] Lin, B., Cheng, T., and Chou, A. (2007). Scheduling in an assembly-type production chain with batch transfer. *Omega*, 35(2):143–151.

[109] Liouane, N., Saad, I., Hammadi, S., and Borne, P. (2007). Ant systems & local search optimization for flexible job shop scheduling production. *International Journal of Computers Communications & Control*, 2(2):174–184.

[110] Lorenzoni, L. L., Ahonen, H., and de Alvarenga, A. G. (2006). A multi-mode resource-constrained scheduling problem in the context of port operations. *Computers & Industrial Engineering*, 50(1):55–65.

[111] Lova, A., Tormos, P., Cervantes, M., and Barber, F. (2009). An efficient hybrid genetic algorithm for scheduling projects with resource constraints and multiple execution modes. *International Journal of Production Economics*, 117(2):302–316.

[112] Lova, A. L., Tormos, M. P., and Barber, F. (2006). Multi-mode resource constrained project scheduling: scheduling schemes, priority rules and mode selection rules. *Inteligencia Artificial, Revista Iberoamericana de Inteligencia Artificial*, 10(30):69–86.

[113] Lozano, A. J. and Medaglia, A. L. (2013). Scheduling of parallel machines with sequence-dependent batches and product incompatibilities in an automotive glass facility. *Journal of Scheduling*, 17(6):521–540.

[114] Malve, S. and Uzsoy, R. (2007). A genetic algorithm for minimizing maximum lateness on parallel identical batch processing machines with dynamic job arrivals and incompatible job families. *Computers & Operations Research*, 34(10):3016–3028.

[115] Mathirajan, M., Chandru, V., and Sivakumar, A. (2007). Heuristic algorithms for scheduling heat-treatment furnaces of steel casting industries. *Sadhana*, 32(5):479–500.

[116] Mati, Y., Lahlou, C., and Dauzere-Peres, S. (2011). Modelling and solving a practical flexible job-shop scheduling problem with blocking constraints. *International Journal of Production Research*, 49(8):2169–2182.

[117] Mati, Y., Rezg, N., and Xie, X. (2001). A taboo search approach for deadlock-free scheduling of automated manufacturing systems. *Journal of Intelligent Manufacturing*, 12(5-6):535–552.

[118] Mati, Y. and Xie, X. (2004). The complexity of two-job shop problems with multi-purpose unrelated machines. *European Journal of Operational Research*, 152(1):159–169.

[119] Mati, Y. and Xie, X. (2008). A genetic-search-guided greedy algorithm for multi-resource shop scheduling with resource flexibility. *IIE Transactions*, 40(12):1228–1240.

[120] Mati, Y. and Xie, X. (2011). Multiresource shop scheduling with resource flexibility and blocking. *IEEE transactions on automation science and engineering*, 8(1):175–189.

[121] Mehta, S. V. and Uzsoy, R. (1998). Minimizing total tardiness on a batch

processing machine with incompatible job families. *IIE transactions*, 30(2):165–178.

[122] Méndez, C., Henning, G., and Cerda, J. (2000). Optimal scheduling of batch plants satisfying multiple product orders with different due-dates. *Computers & Chemical Engineering*, 24(9):2223–2245.

[123] Mendez, C. A. and Cerdá, J. (2004). An milp framework for batch reactive scheduling with limited discrete resources. *Computers & chemical engineering*, 28(6):1059–1068.

[124] Méndez, C. A., Cerdá, J., Grossmann, I. E., Harjunkoski, I., and Fahl, M. (2006). State-of-the-art review of optimization methods for short-term scheduling of batch processes. *Computers & Chemical Engineering*, 30(6):913–946.

[125] Mika, M., Waligóra, G., and Węglarz, J. (2005). Simulated annealing and tabu search for multi-mode resource-constrained project scheduling with positive discounted cash flows and different payment models. *European Journal of Operational Research*, 164(3):639–668.

[126] Mika, M., Waligora, G., and Węglarz, J. (2008). Tabu search for multi-mode resource-constrained project scheduling with schedule-dependent setup times. *European Journal of Operational Research*, 187(3):1238–1250.

[127] Mladenović, N. and Hansen, P. (1997). Variable neighborhood search. *Computers & Operations Research*, 24(11):1097–1100.

[128] Monma, C. L. and Potts, C. N. (1989). On the complexity of scheduling with batch setup times. *Operations Research*, 37(5):798–804.

[129] Monma, C. L. and Potts, C. N. (1993). Analysis of heuristics for preemptive parallel machine scheduling with batch setup times. *Operations Research*, 41(5):981–993.

[130] Moon, S., Park, S., and Lee, W. K. (1996). New milp models for scheduling of multiproduct batch plants under zero-wait policy. *Industrial & engineering chemistry research*, 35(10):3458–3469.

[131] Mori, M. and Tseng, C. C. (1997). A genetic algorithm for multi-mode resource constrained project scheduling problem. *European Journal of Operational Research*, 100(1):134–141.

[132] Moscato, P. et al. (1989). On evolution, search, optimization, genetic algorithms and martial arts: Towards memetic algorithms. *Caltech concurrent computation program, C3P Report*, 826:1989.

[133] Mosheiov, G. and Oron, D. (2008). Open-shop batch scheduling with identical jobs. *European Journal of Operational Research*, 187(3):1282–1292.

[134] Naber, A. and Kolisch, R. (2014). Mip models for resource-constrained project scheduling with flexible resource profiles. *European Journal of Operational Research*, 239(2):335–348.

[135] Naber, A., Kolisch, R., Bianco, L., and Caramia, M. (2014). The resource-constrained project scheduling model of bianco and caramia: clarifications and an alternative model formulation. *Flexible Services and Manufacturing Journal*, 26(3):454.

[136] Nelson, R. T. (1967). Labor and machine limited production systems. *Management Science*, 13(9):648–671.

[137] Neumann, K. and Schwindt, C. (2003). Project scheduling with inventory constraints. *Mathematical Methods of Operations Research*, 56(3):513–533.

[138] Neumann, K., Schwindt, C., and Trautmann, N. (2002). Advanced production scheduling for batch plants in process industries. *OR spectrum*, 24(3):251–279.

[139] Neumann, K., Schwindt, C., and Trautmann, N. (2005). Scheduling of continuous and discontinuous material flows with intermediate storage restrictions. *European Journal of Operational Research*, 165(2):495–509.

[140] Noroozi, A., Mokhtari, H., and Abadi, I. N. K. (2013). Research on computational intelligence algorithms with adaptive learning approach for scheduling problems with batch processing machines. *Neurocomputing*, 101:190–203.

[141] Nudtasomboon, N. and Randhawa, S. U. (1997a). Resource-constrained project scheduling with renewable and non-renewable resources and time-resource tradeoffs. *Computers & Industrial Engineering*, 32(1):227–242.

[142] Nudtasomboon, N. and Randhawa, S. U. (1997b). Resource-constrained project scheduling with renewable and non-renewable resources and time-resource tradeoffs. *Computers & Industrial Engineering*, 32(1):227–242.

[143] Orji, I. M. and Wei, S. (2013). Project scheduling under resource constraints: a recent survey. In *International Journal of Engineering Research and Technology*, volume 2. ESRSA Publications.

[144] Ortiz, M., Neira, D., Jiménez, G., and Hernández, H. (2016). Solving flexible job-shop scheduling problem with transfer batches, setup times and multiple resources in apparel industry. In *International Conference in Swarm Intelligence*, pages 47–58. Springer.

[145] Paksi, A. and Ma'ruf, A. (2016). Flexible job-shop scheduling with dual-resource constraints to minimize tardiness using genetic algorithm. In *IOP Conference Series: Materials Science and Engineering*, volume 114, page 012060. IOP Publishing.

[146] Patterson, J. H. and Roth, G. W. (1976). Scheduling a project under multiple resource constraints: a zero-one programming approach. *AIIE transactions*, 8(4):449–455.

[147] Potts, C. N. and Kovalyov, M. Y. (2000). Scheduling with batching: a review. *European journal of operational research*, 120(2):228–249.

[148] Rajkumar, M., Asokan, P., Anilkumar, N., and Page, T. (2011). A grasp algorithm for flexible job-shop scheduling problem with limited resource constraints. *International Journal of Production Research*, 49(8):2409–2423.

[149] Rajkumar, M., Asokan, P., and Vamsikrishna, V. (2010). A grasp algorithm for flexible job-shop scheduling with maintenance constraints. *International Journal of Production Research*, 48(22):6821–6836.

[150] Rey, G. Z., Bekrar, A., Trentesaux, D., and Zhou, B.-H. (2015). Solving the flexible job-shop just-in-time scheduling problem with quadratic earliness and tardiness costs. *The International Journal of Advanced Manufacturing Technology*, 81(9-12):1871–1891.

[151] Roshanaei, V. (2012). Mathematical modeling and optimization of flexible job shops scheduling problem. *Electronic Theses and Dissertations,University of Windsor*, Paper 157.

[152] Roshanaei, V., Azab, A., and ElMaraghy, H. (2013). Mathematical modeling and a meta-heuristic for flexible job shop scheduling. *International Journal of Production Research*, 51(20):6247–6274.

[153] Sabzehparvar, M. and Seyed-Hosseini, S. M. (2008). A mathematical model for the multi-mode resource-constrained project scheduling problem with mode dependent time lags. *The Journal of Supercomputing*, 44(3):257–273.

[154] Schirmer, A. and Drexl, A. (1997). *Allocation of Partially Renewable Resources: Concept, Models and Applications*. Inst. für Betriebswirtschaftslehre.

[155] Schnell, A. and Hartl, R. F. (2016). On the efficient modeling and solution of the multi-mode resource-constrained project scheduling problem with generalized precedence relations. *OR spectrum*, 38(2):283–303.

[156] Schnell, A. and Hartl, R. F. (2017). On the generalization of constraint programming and boolean satisfiability solving techniques to schedule a resource-

constrained project consisting of multi-mode jobs. *Operations Research Perspectives*, 4:1–11.

[157] Schwindt, C. and Zimmermann, J. (2015). *Handbook on Project Management and Scheduling Vol. 1*. Springer.

[158] Selle, T. (1999). *Lower bounds for project scheduling problems with renewable and cumulative resources*. Inst. für Wirtschaftstheorie und Operations Research.

[159] Shao, X., Liu, W., Liu, Q., and Zhang, C. (2013). Hybrid discrete particle swarm optimization for multi-objective flexible job-shop scheduling problem. *The International Journal of Advanced Manufacturing Technology*, 67(9-12):2885–2901.

[160] Shen, L., Gupta, J. N., and Buscher, U. (2014). Flow shop batching and scheduling with sequence-dependent setup times. *Journal of Scheduling*, 17(4):353–370.

[161] Shen, L., Mönch, L., and Buscher, U. (2013a). An iterative approach for the serial batching problem with parallel machines and job families. *Annals of Operations Research*, 206(1):425–448.

[162] Shen, L., Mönch, L., and Buscher, U. (2013b). A simultaneous and iterative approach for parallel machine scheduling with sequence-dependent family setups. *Journal of Scheduling*, 17(5):471–487.

[163] Shen, X.-N. and Yao, X. (2015). Mathematical modeling and multi-objective evolutionary algorithms applied to dynamic flexible job shop scheduling problems. *Information Sciences*, 298:198–224.

[164] Singh, M. R. and Mahapatra, S. (2012). A swarm optimization approach for flexible flow shop scheduling with multiprocessor tasks. *The International Journal of Advanced Manufacturing Technology*, 62(1-4):267–277.

[165] Singh, M. R., Singh, M., Mahapatra, S., and Jagadev, N. (2015). Particle swarm optimization algorithm embedded with maximum deviation theory for solving multi-objective flexible job shop scheduling problem. *The International Journal of Advanced Manufacturing Technology*, pages 1–14.

[166] Słowiński, R. (1980). Two approaches to problems of resource allocation among project activities-a comparative study. *Journal of the Operational Research Society*, 31(8):711–723.

[167] Słowinski, R. (1981). Multiobjective network scheduling with efficient use of renewable and nonrenewable resources. *European Journal of Operational Research*, 7(3):265–273.

[168] Sprecher, A. and Drexl, A. (1998). Multi-mode resource-constrained project scheduling by a simple, general and powerful sequencing algorithm. *European Journal of Operational Research*, 107(2):431–450.

[169] Sprecher, A., Hartmann, S., and Drexl, A. (1997). An exact algorithm for project scheduling with multiple modes. *OR spectrum*, 19(3):195–203.

[170] Sung, C. S., Kim, Y. H., and Yoon, S. H. (2000). A problem reduction and decomposition approach for scheduling for a flowshop of batch processing machines. *European Journal of Operational Research*, 121(1):179–192.

[171] Talbot, F. B. and Patterson, J. H. (1978). An efficient integer programming algorithm with network cuts for solving resource-constrained scheduling problems. *Management Science*, 24(11):1163–1174.

[172] Tang, L. and Liu, P. (2009). Minimizing makespan in a two-machine flowshop scheduling with batching and release time. *Mathematical and Computer Modelling*, 49(5):1071–1077.

[173] Tareghian, H. R. and Taheri, S. H. (2007). A solution procedure for the discrete time, cost and quality tradeoff problem using electromagnetic scatter search. *Applied Mathematics and Computation*, 190(2):1136–1145.

[174] Tayebi Araghi, M., Jolai, F., and Rabiee, M. (2014). Incorporating learning effect and deterioration for solving a sdst flexible job-shop scheduling problem with a hybrid meta-heuristic approach. *International Journal of Computer Integrated Manufacturing*, 27(8):733–746.

[175] Torabi, S., Karimi, B., and Ghomi, S. F. (2005). The common cycle economic lot scheduling in flexible job shops: The finite horizon case. *International Journal of Production Economics*, 97(1):52–65.

[176] Treleven, M. D. and Elvers, D. A. (1985). An investigation of labor assignment rules in a dual-constrained job shop. *Journal of Operations Management*, 6(1):51–68.

[177] Ulusoy, G., Sivrikaya-Şerifoğlu, F., and Şahin, Ş. (2001). Four payment models for the multi-mode resource constrained project scheduling problem with discounted cash flows. *Annals of Operations Research*, 102(1-4):237–261.

[178] Vaessens, R. J. M., Aarts, E. H., and Lenstra, J. K. (1994). Job shop scheduling by local search. *COSOR Memorandum 94-05*.

[179] Van Peteghem, V. and Vanhoucke, M. (2010). A genetic algorithm for the preemptive and non-preemptive multi-mode resource-constrained project scheduling problem. *European Journal of Operational Research*, 201(2):409–418.

[180] Van Peteghem, V. and Vanhoucke, M. (2014). An experimental investigation of metaheuristics for the multi-mode resource-constrained project scheduling problem on new dataset instances. *European Journal of Operational Research*, 235(1):62–72.

[181] Voß, S. and Witt, A. (2007). Hybrid flow shop scheduling as a multi-mode multi-project scheduling problem with batching requirements: A real-world application. *International journal of production economics*, 105(2):445–458.

[182] Wang, H.-M. and Chou, F.-D. (2010). Solving the parallel batch-processing

machines with different release times, job sizes, and capacity limits by metaheuristics. *Expert Systems with Applications*, 37(2):1510–1521.

[183] Wang, L. and Fang, C. (2012). An effective estimation of distribution algorithm for the multi-mode resource-constrained project scheduling problem. *Computers & Operations Research*, 39(2):449–460.

[184] Wang, Z., Gao, F., Zhai, Q., Guan, X., Liu, K., and Zhou, D. (2012). An integrated optimization model for generation and batch production load scheduling in energy intensive enterprise. In *Power and Energy Society General Meeting, 2012 IEEE*, pages 1–8. IEEE.

[185] Weglarz, J. (1979). Project scheduling with discrete and continuous resources. *IEEE Transactions on Systems, Man, and Cybernetics*, 9(10):644–650.

[186] Węglarz, J. (1981). Project scheduling with continuously-divisible, doubly constrained resources. *Management Science*, 27(9):1040–1053.

[187] Węglarz, J., Józefowska, J., Mika, M., and Waligóra, G. (2011). Project scheduling with finite or infinite number of activity processing modes–a survey. *European Journal of Operational Research*, 208(3):177–205.

[188] Wong, T. C., Chan, F. T., and Chan, L. (2009). A resource-constrained assembly job shop scheduling problem with lot streaming technique. *Computers & Industrial Engineering*, 57(3):983–995.

[189] Xing, L.-N., Chen, Y.-W., Wang, P., Zhao, Q.-S., and Xiong, J. (2010). A knowledge-based ant colony optimization for flexible job shop scheduling problems. *Applied Soft Computing*, 10(3):888–896.

[190] Xiong, J., Chen, Y., and Zhou, Z. (2016). Resilience analysis for project scheduling with renewable resource constraint and uncertain activity durations. *Journal of Industrial and Management Optimization*, 12(2):719–737.

[191] Xu, D., Cheng, Z., Yin, Y., and Li, H. (2009). Makespan minimization for two parallel machines scheduling with a periodic availability constraint. *Computers & Operations Research*, 36(6):1809–1812.

[192] Yazdani, M., Amiri, M., and Zandieh, M. (2010). Flexible job-shop scheduling with parallel variable neighborhood search algorithm. *Expert Systems with Applications*, 37(1):678–687.

[193] Yazdani, M., Zandieh, M., Tavakkoli-Moghaddam, R., and Jolai, F. (2015). Two meta-heuristic algorithms for the dual-resource constrained flexible job-shop scheduling problem. *Scientia Iranica. Transaction E, Industrial Engineering*, 22(3):1242.

[194] Yulianty, A. and Ma'ruf, A. (2013). Predictive approach on flexible job shop scheduling problem considering controllable processing times. *International Journal of Innovation, Management and Technology*, 4(6):565.

[195] Zhang, G., Gao, L., Li, X., and Li, P. (2008). Variable neighborhood genetic algorithm for the flexible job shop scheduling problems. In *International Conference on Intelligent Robotics and Applications*, pages 503–512. Springer.

[196] Zhang, G., Gao, L., and Shi, Y. (2011). An effective genetic algorithm for the flexible job-shop scheduling problem. *Expert Systems with Applications*, 38(4):3563–3573.

[197] Zhang, G., Shao, X., Li, P., and Gao, L. (2009). An effective hybrid particle swarm optimization algorithm for multi-objective flexible job-shop scheduling problem. *Computers & Industrial Engineering*, 56(4):1309–1318.

[198] Zhang, H. and Gu, M. (2009). Modeling job shop scheduling with batches and setup times by timed petri nets. *Mathematical and Computer Modelling*, 49(1):286–294.

[199] Zhang, H., Tam, C., and Li, H. (2006). Multimode project scheduling based

on particle swarm optimization. *Computer-Aided Civil and Infrastructure Engineering*, 21(2):93–103.

[200] Zhang, Q., Manier, H., and Manier, M.-A. (2012). A genetic algorithm with tabu search procedure for flexible job shop scheduling with transportation constraints and bounded processing times. *Computers & Operations Research*, 39(7):1713–1723.

[201] Zheng, X.-l. and Wang, L. (2016). A knowledge-guided fruit fly optimization algorithm for dual resource constrained flexible job-shop scheduling problem. *International Journal of Production Research*, pages 1–13.

[202] Zhu, G., Bard, J. F., and Yu, G. (2006). A branch-and-cut procedure for the multimode resource-constrained project-scheduling problem. *INFORMS Journal on Computing*, 18(3):377–390.

Autobiography

Jobish Vallikavungal Devassia

Candidato para obtener el grado de

Doctor en Ingeniería

con Especialidad en Ingeniería de Sistemas

Universidad Autónoma de Nuevo León

Facultad de Ingeniería Mecánica y Eléctrica

Tesis:

Flexible Jobshop Scheduling Problem with Resource Recovery Constraints

Jobish was born in Mananthavady, a village in India state of Kerala, on April 16, 1988. He is the second son of Devasiya Vallikavunkal Mathai and Annamma. He graduated with a bachelor degree of science in mathematics from Kannur University in 2009. He joined afterward the National Institute of Technology, Calicut and graduated with a master degree in science and technology in mathematics and scientific computing in 2012. In his master studies, his work focused on topological structures in the context of soft sets. He published research articles in international journals and had a growing interest for research. After his master studies, he joined the Vimal Jyothi Engineering College as assistant professor. In 2014, he joined the Universidad Autónoma de Nuevo León, Mexico for his doctoral studies.