

FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Energy-efficient Scheduling for Sustainable Production and Transportation in Flexible Manufacturing Systems

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*“Learn from the ones who came before . . .
and lay the trail, for the ones who come after.”*

Clair-Obscur: Expedition 33

Abstract

The steady growth in energy demand and environmental awareness has placed increasing pressure on manufacturing industries to improve energy efficiency and reduce emissions while coping with volatile electricity costs and stricter environmental regulations. In this context, energy-efficient scheduling has emerged as a cost-effective strategy to achieve sustainability goals without requiring significant investment in new equipment or product design. This has propelled a surge in research on sustainable manufacturing, with a growing number of works focusing on energy-efficient operation scheduling.

This thesis addresses the Energy-Efficient Job Shop Scheduling Problem (EEJSP) and its extensions, focusing on decisions that minimize makespan and energy consumption in bi-objective problems. This research explores multiple energy-saving strategies – namely variable machine and vehicle speed settings – as well as transportation scheduling with limited resources.

Two main goals are pursued. First, the thesis seeks to comprehensively analyze and systematize EEJSP literature, clarifying modelling assumptions, performance measures, and energy-saving strategies and additionally identifying gaps related to the integration of transport. Second, it aims to develop appropriate models and algorithms for relevant EEJSP extensions, namely the EEJSP with limited transportation resources (EEJSPT), which better reflects real-world production settings where optimized scheduling can reduce emissions and energy costs.

Throughout the development of this work, two peer-reviewed journal articles were published, each presented as an individual chapter in this thesis. The first provides a systematic literature review of EEJSP articles, identifying research gaps and highlighting the limited integration of transport and speed-related decisions. The second article introduces both an exact and a heuristic approach to jointly optimize production and transport operations in EEJSPT. The exact approach employs a bi-objective mixed-integer linear programming (MILP) model that, in combination with a lexicographic and ε -constraint method approximates the true Pareto front. The heuristic approach presents a novel multi-population biased random-key genetic algorithm to approximate Pareto-optimal solutions. Computational experiments across multiple test instances demonstrate that coordinated speed control across machines and vehicles can significantly reduce energy consumption with limited impact on makespan, with the test instances having been made publicly available for future research.

Overall, the thesis advances the study of energy-efficient scheduling by providing tools and insights to support sustainable manufacturing decisions through a comprehensive review of EEJSP state of the art, proposing a new and more realistic extension to this problem, and providing a novel MILP problem formulation, a new multi-population genetic algorithm, and benchmark instances.

Keywords: Job shop scheduling, Energy efficiency, Sustainable manufacturing, Optimization, Multi-objective scheduling, MILP, NSGA-II, BRKGA.

Resumo

O crescimento progressivo do consumo energético e desenvolvimento de consciência ambiental têm colocado uma pressão crescente nas indústrias de manufatura para melhorar a eficiência energética e reduzir as emissões, enquanto têm de lidar simultaneamente com custos voláteis de eletricidade e regulações ambientais mais rigorosas.

Neste contexto, o agendamento de produção energeticamente eficiente tem vindo a emergir como uma estratégia eficiente em termos de custo para alcançar objetivos de sustentabilidade sem requerer investimentos significativos em novo equipamento ou design de produtos. Isto potenciou um aumento na investigação sobre produção sustentável, com um número crescente de trabalhos focados em agendamento de produção energeticamente eficiente.

Esta tese aborda o *Energy-efficient Job Shop Scheduling Problem* (EEJSP) e suas extensões, focando-se em decisões que minimizam o makespan e o consumo de energia em problemas bi-objetivo. Este trabalho explora múltiplas estratégias de poupança de energia – nomeadamente definições de velocidade variável de máquinas e veículos – bem como agendamento de transportes com recursos limitados.

Este trabalho tem dois objetivos principais. Primeiro, a tese procura analisar e sistematizar de forma abrangente a literatura de EEJSP, esclarecendo pressupostos de modelação, medidas de desempenho, e estratégias de poupança de energia, e adicionalmente identificar lacunas relacionadas com a integração de transportes. Segundo, pretende desenvolver modelos e algoritmos apropriados para extensões relevantes de EEJSP, nomeadamente o EEJSP com recursos de transporte limitados (EEJSPT), que melhor reflete configurações de produção reais onde o agendamento otimizado de produção pode reduzir emissões e custos de energia.

Ao longo do desenvolvimento deste trabalho, dois artigos de revista com revisão por pares foram publicados, sendo cada um apresentado como um capítulo individual desta tese. O primeiro trata-se de uma revisão sistemática da literatura de EEJSP, identificando lacunas na investigação e destacando a integração limitada de transporte e decisões relacionadas com velocidade neste problema. O segundo artigo introduz abordagens exatas e heurísticas para otimizar simultaneamente as operações de produção e transporte no EEJSPT. A abordagem exata usa um modelo de programação linear inteira (MILP) bi-objetivo que, em combinação com um método lexicográfico e de ε -constraint, consegue uma aproximação da fronteira de Pareto real. A abordagem heurística usa um novo algoritmo genético multi-população – *multi-population Biased random key Genetic Algorithm* – para conseguir boas aproximações da fronteira de Pareto. Testes computacionais em múltiplas instâncias demonstram que o controlo coordenado de velocidade em máquinas e veículos pode reduzir significativamente o consumo de energia com impacto limitado no makespan, tendo

as instâncias de teste usadas sido disponibilizadas publicamente para investigação futura.

De um modo geral, esta tese representa um avanço no estudo de agendamento de produção energeticamente eficiente ao fornecer ferramentas e insights para apoio à decisão em produção sustentável através de uma revisão abrangente do estado da arte de EEJSP, propondo uma extensão nova mais realista para este problema, apresentando um novo modelo MILP para o problema, um novo algoritmo genético multi-população, e novas instâncias de teste.

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Abbreviations and Symbols

AHP	Analytic Hierarchic Process
BRKGA	Biased Random-Key Genetic Algorithm
EEJSP	Energy-Efficient Job Shop Scheduling Problem
EEJSPT	Energy-Efficient Job Shop Scheduling Problem with limited transportation resources
EEJSPT-VSS	Energy-Efficient Job Shop Scheduling Problem with Transportation resources and Variable Speed Settings
EEFJSP	Energy-Efficient Flexible Job Shop Problem
EIA	Energy Information Administration
FCT	Fundação para a Ciência e a Tecnologia
FJSP	Flexible Job Shop Scheduling Problem
JSP	Job Shop Scheduling Problem
JSPT	Job Shop Scheduling Problem with Transportation resources
LU	Load/Unload area
MILP	Mixed-Integer Linear Programming
MS	Variable Machine Speeds
mpBRKGA	Multi-population Biased Random-Key Genetic Algorithm
NP-hard	Nondeterministic Polynomial-time hard
NSGA-II	Non-dominated Sorting Genetic Algorithm II
TEC	Total Energy Consumption

Found in **Energy-Efficient Scheduling in Job Shop Manufacturing Systems: A Literature Review**

ABC	Artificial Bee Colony
ABO	African Buffalo Optimization
ACO	Ant Colony Optimization
AHP	Analytical Hierarchy Process
AMO	Animal Migration Optimization
BA	Bees Algorithm
Bat-	Bat Optimization Algorithm
BBO	Biogeography-Based Optimization
BOA	Bacterial Foraging Optimization Algorithm
BS	Batch Scheduling
BSA	Backtracking Search Algorithm
CD	Crowding Distance
Cmax	Makespan
CP	Constraint Programming
CSO	Cat Swarm Optimization
CT	Total Completion Time of the Jobs
CuS	Customer Satisfaction
DEA	Differential Evolution Algorithm
Dens	Density Estimator
DMS	Distributed Manufacturing Scheduling
DP	Dynamic Programming
DS	Dynamic Scheduling
E	Energy Consumption
EA	Evolutionary Algorithm
EC	Energy Cost
EDA	Estimation of Distribution Algorithm
EEJSP	Energy-Efficient Job Shop Scheduling Problem
EMA	Electromagnetism-like Mechanism Algorithm
EVP	Energy Variable Price
FA	Firefly Algorithm
FFO	Fruit Fly Optimization
FJSP	Flexible Job Shop Scheduling Problem
GA	Genetic Algorithm
GD	Generational Distance
GEP	Gene Expression Programming
GP	Genetic Programming
GRASP	Greedy Randomized Adaptive Search Procedure
GSO	Glow-worm Swarm Optimization
GWO	Grey Wolf Optimization
HSA	Harmony Search Algorithm
HV	Hypervolume
I/O	On&Off
ICA	Imperialist Competitive Algorithm

Id	Idle Time Energy Consumption
IGD	Inverted Generational Distance
ILS	Iterated Local Search
In	Indirect Energy Consumption
IoMT	Internet of Manufacturing Things
JA	Jaya Algorithm
JPP	Job Process Planning
JSP	Job Shop Scheduling Problem
LC	Labour Cost
Learn	Learning Methods
Lexic	Lexicographic
LOP	Layout Optimization Problem
MA	Memetic Algorithm
MaS	Maintenance Scheduling
MBO	Migrating Birds Optimization
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
ML	Total Machine Workload
ML mean	Mean Machine Workload
MLmax	Maximum Machine Workload
moEA	Multi-objective Evolutionary Algorithm
moGA	Multi-objective Genetic Algorithm
moPSO	Multi-objective Particle Swarm Optimization
MS	Machine Speed
N	Noise
NDS	Non-Dominated Sets
NPA	Nested Partitions Algorithm
NSGAI	Non-dominated Sorting Genetic Algorithm II
P	Processing Energy Consumption
PC	Total Production Cost
PP	Peak Power Consumption
PSO	Particle Swarm Optimization
Q	Quality
QEA	Quantum Evolutionary Algorithm
RD	Rescheduling Disruptions
ReL	Reliability
RM	Raw Material Consumption
RPD	Reference Point Direction
S	Setup Energy Consumption
SA	Simulated Annealing
SDST	Sequence-Dependent Setup Time
SFLA	Shuffled Frog-Leaping Algorithm
Simul	Simulation

SPEAII	Strength Pareto Evolutionary Algorithm II
Sum	Summation of the Objective Functions
T	Total Tardiness
T mean	Mean Tardiness
TC	Total Carbon Emission
Tcost	Cost of Total Tardiness
TE	Total Tardiness + Earliness
Tmax	Maximum Tardiness
Tr	Transportation Energy Consumption
TrS	Transport Scheduling
TrT	Transport Time
TS	Tabu Search
VNS	Variable Neighborhood Search
WIP	Work In Progress
WOA	Whale Optimization Algorithm
WoS	Worker Scheduling
wSum	Summation of Weighted Objective Functions
Norm wSum	Summation of Weighted Normalized Objective Functions
wT	Total Weighted Tardiness
wTE	Total Weighted Tardiness + Earliness
WWO	Water Wave Optimization

Found in **Energy-efficient Job Shop Scheduling Problem with Transport Resources considering Speed Adjustable Resources**

AGVs - automated guided vehicles
BPX - biased parameterised uniform crossover
BRKGAs - Biased random key genetic algorithms
CD - crowding distance
EEJSP - energy-efficient job shop scheduling problem
EEJSPT - energy-efficient job shop scheduling problem with transport resources
GD - modified Generational Distance
GD+ - modified Generational Distance
Gmax - predetermined number of generations
GSAA - Genetic and Simulated Annealing Algorithm
GWO - grey wolf optimisation
HV - Hypervolume
IoMT - Internet of Manufacturing Things
JSP - Job shop scheduling problem
JSPT - job shop scheduling problem with transport resources
LU - load/unload area
m/s - metres per second
MILP - Mixed-Integer Linear Programming
multi-objective mpBRKGA - multi-objective multi-population biased random key genetic algorithm
NSGA-II - Non-dominated Sorting Genetic Algorithm II
PF - Pareto fronts
PF★ - true Pareto front
PFs - Pareto fronts
PF* - true Pareto front
RKGAs - Random key genetic algorithms
RKs - random keys
SA - simulated annealing
SMEs - small and medium enterprises

Chapter 1

Introduction and Overview

This document presents the dissertation for the Ph.D. of the student João Fernandes, under the supervision of Professors Dalila Martins Fontes and Mahdi Homayouni, in the Doctoral Program in Engineering and Industrial Management at the Faculty of Engineering of the University of Porto.

1 Problem setting and motivation

The industrial sector, which includes manufacturing, refining, mining, agriculture, and construction, accounts for over 50% of worldwide end-use energy consumption [[U.S. Energy Information Administration \(EIA\), 2021](#)]. Under rising energy demand, stricter environmental requirements, and volatile energy costs, manufacturers are increasingly pressured to improve energy efficiency while preserving productivity. Sustainable manufacturing responds to this challenge by promoting economically sound production processes that reduce environmental impacts and conserve energy and natural resources [[Le Hesran et al., 2019](#), [Fernandes et al., 2022](#), [U.S. Environmental Protection Agency, 2025](#)].

Scheduling is a particularly attractive lever because it can improve resource use with comparatively low investment, which is especially relevant for small and medium-sized enterprises [[Gahm et al., 2016](#), [Zheng et al., 2014](#), [Zhou et al., 2018](#)]. As defined by [Pinedo \[2016\]](#), scheduling allocates resources to tasks over time to optimize one or more objectives. In manufacturing, these decisions include assigning and sequencing operations on machines, selecting processing speeds, and coordinating transportation tasks [[Gahm et al., 2016](#), [Nouri et al., 2016](#)]. Energy-efficient scheduling therefore seeks to reduce energy consumption, peak power demand, carbon emissions, and energy costs while maintaining service levels [[Fernandes et al., 2022](#)]. Over the last decade, research on energy-efficient scheduling has increasingly examined bi-objective formulations that balance time-based

performance, such as makespan, with energy-related objectives, such as total energy consumption or peak power consumption. These studies show that well-optimized schedules can reduce processing and non-processing energy, often with limited impact on throughput.

Despite this growth, most works treat machine scheduling in isolation, leaving important aspects of the manufacturing system—notably the explicit handling of transportation resources and the combined use of several energy-saving strategies—largely unaddressed [Fernandes et al., 2022]. These limitations are examined in detail in Section 1.3 and motivate the research objectives stated in Section 2. This thesis adopts a more integrated approach, investigating energy-efficient scheduling in job shop environments that explicitly model both production and (internal) transportation decisions while simultaneously considering variable speed settings for both machines and vehicles. The central premise is that jointly optimizing production and transportation scheduling, along with resource speed levels, enables significant energy reductions with little impact on makespan, and, in specific instances, even improvements in both objectives [Fontes et al., 2024].

1.1 Job Shop Scheduling Problem

This section briefly introduces the Job Shop Scheduling Problem (JSP), which provides the basis for the energy-efficient and transport-related extensions studied in this thesis.

The Job Shop Scheduling Problem (JSP) is a classical combinatorial optimization problem in which n jobs, each consisting of an ordered sequence of operations, must be scheduled on m machines, where each operation requires a distinct machine for a fixed duration, no preemption is allowed, and each machine processes at most one operation at a time. The JSP is a notoriously difficult problem, classified as NP-hard and often used as a comparative testbed for different solution techniques [Jain and Meeran, 1998]. It has been an extensively studied problem for over half a century due to its numerous applications in areas such as operations research and computer science [Błażewicz et al., 1996]. The JSP is particularly relevant for the manufacturing industry, where optimizing production scheduling can vastly increase throughput and reduce costs [Jones and Rabelo, 1998], and is applicable both to small and large businesses.

Formally, the JSP can be described as follows:

A set J of jobs must be processed without preemption on a set I of machines. Each job $j \in J$ comprises a set $O_j = \{o_{j1}, o_{j2}, \dots, o_{(j n_j)}\}$ of n_j ordered production operations. Let $N = \sum_{j \in J} n_j$ be the total number of operations and let $O = \cup_{j \in J} O_j$ be the set of all operations across all jobs.

Each operation $l \in O$ requires a processing time π_l and must be processed on a specific machine m_l . Once an operation begins on a machine, it cannot be interrupted until completion. Each machine can only process one operation at a time and each job can only be processed on one machine at a time.

The goal is to find a sequence of operations for each machine that optimizes some performance measure, while satisfying precedence constraints between operations. Although several performance measures can be defined, the most commonly used one is the makespan, that is, the time required to complete all operations of all jobs [Manne, 1960].

1.2 Energy-efficient Job Shop Scheduling Problem

To address rising energy costs and environmental targets, many authors have extended the JSP by incorporating energy considerations. Multiple authors such as Jiang et al. [2018], Dai et al. [2019] and He et al. [2021] referred to this extension as the Energy-Efficient Job Shop Scheduling Problem (EEJSP).

The EEJSP is one of the main problems covered in this thesis and is the focus of the literature review article reproduced in Chapter 2. This subsection defines the problem and its main characteristics.

The EEJSP extends the JSP by incorporating energy use and/or energy cost into the objective function(s), often alongside traditional criteria such as makespan or tardiness [Fernandes et al., 2022]. As an extension of the classic JSP, the EEJSP usually considers machine energy consumption and optimizes the total energy consumption (TEC) through operation sequencing [Akbar and Irohara, 2018].

In its simplest form, the EEJSP retains all the previously mentioned characteristics of the JSP. In addition, it considers that each operation $l \in O$ requires an amount of processing energy e_l determined by the machine's power consumption and the operation's processing time. While these characteristics are common to all works on the EEJSP, further features, constraints, and decisions may be included, depending on the variant under consideration.

As described by Fernandes et al. [2022], about two-thirds of EEJSP studies are multi-objective, with at least one energy-related objective, such as TEC, energy cost, carbon emissions, or peak power consumption. These works usually optimize job sequencing and operation start/completion times. The remaining studies add decisions such as machine speed selection, machine on/off status, or tariff-dependent time-slot allocation, each giving rise to a specific EEJSP extension.

Among these extensions, the consideration of variable machine speeds (MS) is the one most thoroughly explored in this thesis. In the EEJSP with MS, machines can operate at discrete (or continuous) speed levels, creating a time-energy trade-off: lower speeds typically reduce power draw but increase processing time. Adjusting machine speed can therefore be used as an energy saving measure and can materially reduce energy without undue productivity loss [Luo et al., 2020, Salido et al., 2016, Yin et al., 2017]. This is achieved by speeding up operations on the critical path (shortening the makespan) while slowing down other operations (reducing energy consumption). This strategy is commonly employed in

CNC machining contexts and has been repeatedly modeled in EEJSP studies [[Fernandes et al., 2022](#)].

This subsection has introduced the EEJSP and its characteristics, providing the foundation for the subsequent extensions in this thesis. These extensions and the associated energy-saving strategies are elaborated upon in the literature review article in Chapter 2.

1.3 Energy-Efficient Job Shop Scheduling Problem with Transportation resources

This subsection introduces the Energy-Efficient Job Shop Scheduling Problem with Transportation resources (EEJSPT), an extension of the EEJSP that provides the foundation for the novel problem studied in Chapter 3. It first discusses the Job Shop Scheduling Problem with Transportation resources (JSPT) and then incorporates energy-efficiency considerations.

In recent years, a JSP variant that has garnered increasing attention is the Job Shop Scheduling Problem with Transportation resources (JSPT). The scheduling of job operations on machines and the scheduling of job transportation around the shop floor are typically treated as separate. Nevertheless, several works integrate these two problems. The first such work seems to have been that of [Bilge and Ulusoy \[1995\]](#). Since then, several researchers have tackled this problem, although many have proposed solution approaches in which machine and transport scheduling are solved sequentially. For example, [Ulusoy et al. \[1997\]](#), [Abdelmaguid et al. \[2004\]](#) and [Reddy and Rao \[2006\]](#) first determine the sequence of operations for each machine, and then derive the transport sequence. More recently, solution approaches that simultaneously determine operations and transport scheduling have been proposed, see e.g., [Fontes and Homayouni \[2019\]](#), [Ham \[2021\]](#).

These works address major literature limitations regarding transportation in the JSP:

- Disregarding travel times: In many works, the travel time between machines is ignored; this may compromise the feasibility, or at least the accuracy, of the production plan, since the starting time of each operation and the makespan of the production plan are unrealistic. As a result, production capabilities are likely to be overestimated and orders may fail to be completed on time, especially in production settings where travel times are significant relative to processing times.
- Embedding travel times in processing times: A common workaround is to incorporate travel times into operation processing times. This implicitly assumes that the time between the end of an operation and the start of the next operation of the same job is known beforehand and is unaffected by scheduling decisions. Such an assumption is only valid when travel times are constant and there is unlimited vehicle availability. In real systems, the number of vehicles is limited and thus, they may not be available

to pick up jobs immediately upon operation completion. Hence, the time between consecutive operations of the same job may not be constant, as it depends on both vehicle availability and vehicle scheduling. As such, this strategy leads to production delays, since vehicle availability cannot always be ensured.

- Assuming unlimited vehicle availability. Many works consider that vehicles are always available, an assumption which is unrealistic and, as noted above, may lead to production delays.

By combining both the concepts of energy-efficiency from EEJSP and transportation from JSPT, a new problem can be defined: the Energy-Efficient Job Shop Scheduling problem with Transportation resources (EEJSPT). This new problem incorporates a fleet of vehicles and travel times into the EEJSP. In addition to the EEJSP definition presented in Section 1.2, the following is added: the EEJSPT includes a set A of identical vehicles that transport the jobs between machines, as well as to and from the Load/Unload area (LU). All jobs and vehicles are initially located at the LU. Vehicles follow predefined paths between locations (LU and machines), move at a constant speed regardless of whether they are loaded or empty, and can carry at most one job at a time. Transport operations are non-preemptive and travel times are constant, as congestion issues are not considered.

When a vehicle arrives at a machine, the job is immediately delivered to the machine's input buffer, which, as usual, is assumed to have sufficient capacity, and the vehicle may immediately proceed to its next assignment. Similarly, once an operation is completed, the machine can start processing its next operation, if available. The job is either loaded onto a vehicle for transport or placed in the machine's output buffer, where it waits if no vehicle is currently available. A vehicle journey always involves a loaded trip to deliver a job and may then involve an empty trip if the vehicle location is different from that of the job it needs to pick up.

The objective of the EEJSPT is to minimize both the TEC and makespan of the overall production plan by simultaneously scheduling machine operations and vehicle tasks (transport operations). The makespan now also includes, for each job, the time required for its initial transport from the LU to the machine processing its first operation.

1.4 Energy-Efficient Job Shop Scheduling Problem with Transportation resources and Variable speed settings

This subsection introduces the Energy-Efficient Job Shop Scheduling Problem with Transportation resources and Variable Speed Settings (EEJSPT-VSS), the novel extension studied in Chapter 3.

The EEJSPT-VSS extends the EEJSPT by introducing variable speed settings for both machine operations and vehicle tasks. Variable speed settings in JSP and EEJSP contexts

have already been considered in several works; in the latter case, the variant is often referred to as the EEJSP with variable machine speeds (MS) or EEJSP-MS.

Compared with the EEJSPT, the main change is that both machines and vehicles can operate at different speed levels. For each operation $l \in O$, the set of admissible machine speed levels is denoted by P_l . If operation l is processed at speed level $p \in P_l$, its processing time is π_l^p and the corresponding machine power consumption is e_l^p ; hence, its processing energy is $e_l^p \times \pi_l^p$.

An important property of this energy model is that the power consumption e_l^p is, in general, a non-linear function of the speed level. For industrial machines and vehicles, faster operation requires disproportionately more power, so that doubling the speed does not double the power draw but typically results in a substantially larger increase; the same holds for vehicle traction power, which grows non-linearly with travel speed. As a consequence, the energy savings achieved by lowering a speed level are not proportional to the additional time incurred, and the trade-off between makespan and total energy consumption induced by speed selection is itself non-linear. This non-linearity is one of the main sources of structural difficulty in the EEJSPT-VSS: were the speed–power relationship linear, the energy implications of speed selection would reduce to a simple function of distance or processing time, and the speed-level decisions could be made largely independently of the sequencing decisions, considerably simplifying both the MILP formulation and the heuristic search.

In this problem a machine cannot be turned off until all operations assigned to it have been completed. Between operations, machines are considered to be in a “stand-by” mode, with negligible energy consumption.

As in the EEJSPT, a set of A identical vehicles is used to transport the jobs between machines and the LU area and any vehicle can transport any job. However, in the EEJSPT-VSS, vehicles can travel at any of the average speed levels in a set V with a predefined, speed level dependent power consumption. The power consumption also depends on whether the vehicle is traveling empty or loaded (carrying a job). Since the floor layout is known and the transport tasks are non-preemptive, the travel time and energy consumption between any two locations (at a specific average speed level) are known for both empty and loaded journeys. For each leg of a transportation task (either loaded or empty) the speed setting of a vehicle – which sets the average vehicle speed for that leg – is chosen independently.

The objective is to minimize both makespan and TEC by jointly sequencing machine operations and vehicle tasks, assigning vehicles to transport operations, and selecting speed levels for machine operations and vehicle legs. This subsection has introduced a novel EEJSPT extension that incorporates variable machine and vehicle speeds which had not been tackled prior to [Fontes et al. \[2024\]](#).

Although the Flexible Job Shop Problem (FJSP)—which generalizes the JSP by allowing each operation to be processed on one of several eligible machines—has received con-

siderable attention in the energy-efficient scheduling literature, this thesis remains within the (non-flexible) job shop setting. The reason is one of scope and tractability. The FJSP's machine-assignment decision, added on top of the integration of finite transportation resources and variable speed settings for both machines and vehicles, would substantially enlarge the solution space and complicate both the formulation of a tractable MILP model and the design of effective metaheuristics. Since the joint integration of finite transportation resources and variable speed settings into the EEJSP was already novel with respect to the state of the art at the time, this thesis adopts an incremental scoping decision: the FJSP layer is deliberately left out, so that the contribution can focus on the joint treatment of transportation resources and speed-adjustable machines and vehicles. Extending the EEJSPT-VSS to a flexible job shop setting is identified as a direction for future research and discussed in Chapter 4.

2 Research objectives and questions

Energy-efficient manufacturing systems can improve environmental and economic performance, robustness, and public reputation [Giret et al., 2015]. Developing scheduling problems that incorporate realistic operating limitations can therefore support more effective optimization tools for industry.

The comprehensive review by Fernandes et al. [2022], reproduced in Chapter 2, identified three main gaps: the omission or oversimplification of transportation resources, especially under limited vehicle availability; the limited joint use of multiple energy-saving strategies, such as variable speed settings; and the lack of standardized benchmark instances for EEJSP extensions. These gaps motivate the research objectives that follow.

The thesis has two main objectives:

Research Objective 1:

Present a structured and critical literature review on EEJSP.

Achieving this first objective entailed conducting a systematic review and synthesis of the existing literature on energy-efficient job shop scheduling problems (EEJSP) and closely related variants, including job shop scheduling with transportation resources. This involved classifying modeling approaches, energy-related objectives, energy-saving strategies (e.g., variable speed settings, switching machines off), and solution methods (exact and heuristic), as well as identifying the main research gaps and avenues for further research. The corresponding results are reported in the review paper included in Chapter 2, which provides the

foundation for subsequent contributions of this thesis.

Research Objective 2:

Propose a novel EEJSP extension that addresses key research gaps and provides exact and heuristic solution methods for the new problem.

The second objective is to propose and solve a novel EEJSP extension that addresses the identified gaps. The proposed EEJSPT-VSS introduces finite transport resources and variable speed settings for both machine operations and vehicle tasks.

The full problem description, including the role of variable speed settings for both machines and vehicles, is given in Section 1.4. Significant reductions in energy consumption are expected through the coordinated optimization of operation sequencing, transport allocation, and speed-level selection.

Achieving this objective entails:

- (i) developing an exact solution approach to approximate the Pareto front for the EEJSPT-VSS, based on a bi-objective mixed-integer linear programming model that minimizes makespan and total energy consumption, combined with lexicographic and ε -constraint methods;
- (ii) developing a multi-objective genetic algorithm to efficiently approximate the Pareto front for larger problem instances;
- (iii) performing computational experiments to evaluate the performance of the proposed methods and to characterize the trade-offs between production time and energy consumption under different speed scenarios.

The main outcomes of this second objective are presented in the paper included as Chapter 3 of this thesis.

Research question

Based on the identified literature and research gaps, the research question proposed is the following:

Can energy efficiency and production performance be jointly improved through optimized scheduling in job shop environments with transportation constraints, where both machine operations and vehicle transport tasks can be processed at variable speeds?

In line with this question the thesis adopts the following Hypothesis:

Hypothesis:

Energy efficiency and production performance can be jointly improved in an EEJSPT environment where machines and vehicles operate at variable speeds, through the development and implementation of appropriate mathematical models and heuristics.

3 Methodology Overview

The methodology employed for this work was designed to address the objectives outlined in Section 2 : first, to systematize the existing literature on EEJSP and closely related problems; and second, to address the most pressing gaps identified through the development of new models and solution methods.

Broadly, the work is organized into two parts, namely: a systematic literature review, and the development and analysis of models and heuristics for the EEJSPT-VSS.

Literature review

The first step conducted for this research was an extensive literature review on the Energy-Efficient Job Shop Scheduling Problem (EEJSP) and the Energy-Efficient Flexible Job shop Problem (EEFJSP). This was done by gathering relevant works through initial keyword searches in Scopus [Elsevier, 2022] and Web of Science [Clarivate, 2022]. These searches were complemented with subsequent backward and forward reference searches to capture additional works accounting for varying authors' keyword choices.

The combined set of works was then cleaned by removing duplicates and iteratively trimming down based on title and abstract relevance. The remaining papers were read in full and analyzed in detail. The full detailed process, including search strings, inclusion and exclusion criteria, and classification scheme is described in Fernandes et al. [2022], reproduced as Chapter 2 of this thesis.

The review process and its outcomes, including the identification of the research gaps stated in Section 2 , are described in detail in Fernandes et al. [2022] and reproduced in Chapter 2. These outcomes informed the research questions, hypothesis, and objectives that guide the remainder of the thesis.

Development of models and heuristics for EEJSPT-VSS

Transportation resources and variable speed settings were selected as the key extensions for the new problem variant, leading to the definition of the EEJSPT-VSS.

To achieve the second objective, a bi-objective MILP model was formulated to represent scheduling decisions and minimize makespan and TEC. The model is solved through a lexicographic procedure combined with an ε -constraint scheme, producing high-quality reference solutions for small instances and benchmarks for the proposed metaheuristic.

4 Document Structure and Synopsis

The thesis is structured as a collection of papers, complemented by introductory and concluding chapters that frame and integrate the contributions. It is organized into four main chapters.

Chapter 1

Chapter 1 establishes the problem setting, presents the research objectives, question, and hypothesis, and outlines the methodology and document structure. It also introduces background on the JSP and the EEJSP variants addressed in this thesis.

Chapter 2

Chapter 2 reproduces the published journal paper *Energy-Efficient Scheduling in Job Shop Manufacturing Systems: A Literature Review*, a structured survey of 172 papers published between 2013 and 2022. The detailed contributions of this paper are summarized in Section 5.

Chapter 3

Chapter 3 reproduces the published journal paper *Energy-Efficient Job Shop Scheduling Problem with Transport Resources considering Speed-Adjustable Resources*, which introduces the EEJSPT-VSS together with exact and metaheuristic solution methods. The detailed contributions of this paper are summarized in Section 5.

Chapter 4

Chapter 4 synthesizes the main findings, discusses theoretical and practical implications, identifies limitations, and outlines directions for future research.

5 Main Contributions

As a whole, the work developed in this thesis advances the state of the art in EEJSP, with the most significant contributions embodied in the two published papers and in the benchmark instances made publicly available for future research.

This section highlights the contribution of each paper individually and then summarizes the overall contributions of the thesis.

Contribution of the literature review paper [Fernandes et al., 2022]

Beyond mapping and categorizing the existing literature on EEJSP and EEJSP, the review makes several scientific contributions: First, it consolidates and clarifies terminology and variant definitions for the EEJSP and related problems, helping to reduce fragmentation in the literature due to lack of standardized naming conventions. Second, it systematically analyzes and compares the modeling assumptions and performance metrics used in the surveyed works, highlighting the lack of standardized benchmarks and reporting practices. Third, it identifies the key research gaps in the EEJSP literature presented in Section 2, which directly motivated the remainder of the thesis.

The review also contributes to research infrastructure by compiling and publicizing the existing benchmark instances for selected EEJSP variants, thereby supporting comparability and reproducibility in future studies. Overall, this work provides a comprehensive state-of-the-art overview and a clear research agenda.

Contribution of the EEJSPT-VSS paper [Fontes et al., 2024]

The second paper introduces and formalizes the EEJSPT-VSS, a novel EEJSP variant with limited transportation resources and speed-adjustable machines and vehicles. It proposes a bi-objective MILP model and an exact solution approach combining lexicographic optimization with an ϵ -constraint strategy to approximate reference Pareto fronts for small instances. It also develops a multi-objective, multi-population Biased Random-Key Genetic Algorithm (mpBRKGA), which outperforms an NSGA-II in approximating the reference fronts at lower computational cost.

The paper further provides two publicly available sets of benchmark instances and shows that coordinated speed adjustment for machines and vehicles can improve energy consumption and, in some cases, makespan. From an application viewpoint, the work

is relevant for flexible manufacturing systems using automated or semi-automated transport resources, where joint optimization of production scheduling, vehicle assignment, and speed decisions can support both productivity and energy efficiency.

Contributions of the thesis as a whole

Taken together, the two main publications contribute to the thesis objectives in several complementary ways:

- Establishing a comprehensive, structured view of energy-efficient scheduling in job shop manufacturing systems, clarifying the main problem variants, modeling choices, solution approaches, and existing benchmark instances, as well as identifying research gaps in EEJSP and EEJSPT literature.
- Introducing a novel EEJSP extension in EEJSPT-VSS, a realistic and challenging problem that integrates production and transport scheduling with variable speed settings for both machines and vehicles.
- Proposing and testing exact and heuristic methods for this novel extension - a MILP model, as well as a novel multi-population mpBRKGA. The latter is an algorithmic framework applicable to other multi-objective problems and has been shown to perform well for the problem considered.
- Providing benchmark instances and computational results for EEJSPT-VSS, enabling other researchers to compare solution methods and build on the numerical findings, contributing to improved transparency and reproducibility of research in this area.
- Providing insights and evidence on ways to leverage speed-adjustable resources for joint improvements in makespan and energy consumption, contributing to more sustainable production and transport planning in flexible manufacturing systems, particularly for small and medium-sized enterprises

Overall, the thesis advances the modeling and solution of integrated, energy-aware production and transport scheduling problems, while providing data, tools, and insights for more environmentally friendly and efficient manufacturing systems.

The chapters that follow build directly on this foundation, beginning with the systematic literature review in Chapter [2](#).

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Chapter 2

Energy-Efficient Scheduling in Job Shop Manufacturing Systems: A Literature Review

Energy-Efficient Scheduling in Job Shop Manufacturing Systems: A Literature Review

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Energy efficiency has become a major concern for manufacturing companies not only due to the environmental concerns and stringer regulations but also due to the large and incremental energy costs. Energy-efficient scheduling can be effective at improving energy efficiency and thus reducing energy consumption and associated costs as well as pollutant emissions. This work reviews recent literature on energy-efficient scheduling in job shop manufacturing systems with a particular focus on metaheuristics. We review 172 papers published between 2013 and 2022, by analyzing the shop floor type, the energy efficiency strategy, the objective function(s), the newly added problem feature(s), and the solution approach(es). We also report on the existing data sets and make them available to the research community. The paper is concluded by pointing out potential directions for future research, namely developing integrated scheduling approaches for interconnected problems,

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fast metaheuristic methods to respond to dynamic scheduling problems, and hybrid metaheuristic and big data methods for cyber-physical production systems.

Keywords: Job shop scheduling problem · Flexible · Scheduling · Energy efficiency · Literature review

1 Introduction

According to the 2021 U.S. Energy Information Administration's International Energy Outlook, the industrial sector including refining, mining, manufacturing, agriculture, and construction accounts for more than 50% of end-use energy consumption. Although it dropped by a few percentage points in 2020, due to the effects of the COVID-19 pandemic, energy consumption is projected to increase from its current 245 quadrillion British thermal units (BTUs) to over 360 quadrillion BTUs in 2050 (a 45% increase) [U.S. Energy Information Administration, 2021].

Due to a steady increase in both energy demand and environmental awareness, the industrial sector faces additional challenges including stricter regulations and volatile energy costs. Thus, manufacturing companies need to reduce the energy consumption, which can be accomplished through the use of new equipment and better process and product design. However, researchers have proved energy-efficient scheduling to be an effective way of reducing energy consumption. Additionally, energy-efficient scheduling has the advantage of not requiring a significant investment, if at all, which is particularly relevant for small and medium enterprises [Para et al., 2022, Bansch et al., 2021, Gao et al., 2020, Akbar and Irohara, 2018, Gahm et al., 2016].

Scheduling is the process of allocating scarce resources to tasks over time and it is one of the success factors of a manufacturing system since it may have a considerable impact on the system performance. Energy-efficient scheduling attempts to lower energy consumption while providing the same level of service.

In recent years, several researchers have addressed energy-efficient scheduling problems; some by imposing energy related constraints or objectives He et al. [2015], Mokhtari and Hasani [2017], Piroozfard et al. [2018], Wang et al. [2018a], Dai et al. [2019], Zhang et al. [2017c], Gong et al. [2018], Dai et al. [2015], Lei and Guo [2015], Zhang et al. [2015], Wang et al. [2018b], Liu et al. [2017], Jiang et al. [2014], Liu et al. [2019], Zhang et al. [2016], Xu et al. [2016] and others by extending the scope of problem decisions to include equipment status Liu et al. [2014], Wu and Sun [2018], Liu et al. [2016], May et al. [2015], Meng et al. [2019a], Pach et al. [2014], Zhang et al. [2017b], equipment working speed [Zhang and Chiong, 2016, Lei et al., 2017, Yin et al., 2017b, Salido et al., 2016b, Tang and Dai, 2015], and time slot allocation [Gong et al., 2019, Zhang et al., 2017a, Far et al., 2019, Hemmati Far et al., 2018]. We review all works on energy-efficient job shop scheduling problems regardless of how energy consumption is approached (optimized or restricted) and how energy consumption is changed (equipment status or working speed).

The purpose of this work is to provide a comprehensive review of the main research efforts and achievements regarding energy-efficient scheduling in job shop manufacturing systems with an emphasis on metaheuristic approaches. Additionally, it can be further regarded as an essential update and extension of existing reviews; this way providing a struc-

tured guideline for future practices and future research. Lastly, it also aims at facilitating solution comparisons in future work by creating a publicly available library of benchmark instances of energy-efficient job shop scheduling problems.

Scheduling problems in manufacturing systems are, in general, NP-hard; thus, their energy-efficient versions are also NP-hard [Garey et al., 1976]. Exact optimization approaches can only solve efficiently small-sized problem instances. Therefore, most of the literature proposes (meta)heuristic solution approaches.

Although there is a large number of interesting manufacturing scheduling problems, this review focuses on the job shop manufacturing environment as a large and important segment of the industry uses such shop floor type. The classical job shop scheduling problem (JSP) comprises a set of jobs and a set of machines. Each job consists of a sequence of manufacturing operations that must be processed in a given order. The JSP considers that each operation must be processed on a given machine. In contrast, in the flexible job shop scheduling problem (FJSP) there are several machines that can process each operation of each job. Therefore, to solve the FJSP, one also has to determine which machine processes each operation, i.e., job routing.

The increasing number of publications concerned with sustainable manufacturing led to the publication of several reviews. As described in Bansch et al. [2021], early reviews focus on concepts and technologies and more recent ones address i) specific aspects of energy-aware production planning, such as power load scheduling Cui and Zhou [2018], electric storage systems Weitzel and Glock [2018], smart grid Rathor and Saxena [2020], and waste minimization Le Hesran et al. [2019]; ii) specific approaches, such as approaches in multi-objective environments Giret et al. [2015], simulation Garwood et al. [2018], and machine learning Narciso and Martins [2020]; iii) sustainable practices [Renna and Materi, 2021, Waltersmann et al., 2021, Le Hesran et al., 2019]; or iv) general manufacturing systems [Gao et al., 2020, Akbar and Irohara, 2018, Gahm et al., 2016, Giret et al., 2015, Bansch et al., 2021].

The contributions of this work can be summarized as i) to collect in a single source all recent relevant contributions to energy-efficient scheduling in job shop manufacturing systems, ii) to summarize current research findings, iii) to outline the significance of the work done in a range of contexts, iv) to identify possible future research directions, and v) to create and make available to the research community a web-library with existing data sets that can be used as benchmark instances in future studies.

The remainder of this work is organized as follows. Section 2 describes the scope of this review and the criteria used to select the papers. In Section 3, we provide a brief analysis of the 172 papers reviewed and, in Section 4, we discuss the different features incorporated in recent energy-efficient scheduling research. Section 5 presents solution approaches developed for energy-efficient scheduling problems in job shop environments. Moreover, in

Section 6, we provide a review of the literature benchmark problem instances. Finally, literature gaps, topics for future research, and some conclusion remarks are presented in Section 7.

2 Review scope and methodology

Scheduling problems involving energy have been increasingly attracting the attention of researchers and practitioners. Due to the large volume of literature, we focus on the papers published in English that explicitly address energy efficiency and propose scheduling methods within job shop manufacturing systems. In other words, the papers considering sustainability objectives other than energy efficiency are out of the scope of this work. (For a detailed breakdown of the various research clusters regarding sustainable manufacturing the reader is referred to [Akbar and Irohara, 2018, Le Hesran et al., 2019].) Also out of the scope of this review are works tackling higher levels of decision-making (mid and long-term), such as logistics, supply chain management, and business management; even if focusing on energy efficiency. (A review on such works can be found in [Biel and Glock, 2016].) Finally, our search is limited to journal papers and book chapters; thus, excluding publications in the form of conference proceedings.

The review process used consists of the following six stages:

- i. scope definition - described in the previous paragraphs;
- ii. keywords definition - extracted from recent literature (review and research papers) by a heuristic search;
- iii. structured search (data gathering) - bibliographic databases were searched using the keywords found in stage ii. (in a generic format and considering both American and English spellings) and considering the date range 2011-2022;
- iv. data structuring and organizing - the set of records resulting from the structured search were then combined, screened, and cleaned as explained below;
- v. search expansion (additional data gathering by backward/forward reference search) - works citing and works cited by the set of works resulting from stage iv. were added and the new set of records was then subject to structuring and organizing, stage iv. (stages iv. and v. were repeated several times until the set of records remained unchanged); and
- vi. bibliography classification and analysis - reported in the following sections.

We searched for published papers, dating back to 2011¹, that included in the title, in the abstract, or in the list of keywords the following combinations of generic keywords (stage ii.):

("*machin*" or "production*" or "operation*", "manufactur*" or "job-shop*" or "jobshop*" or "job shop*", or "flexib*")

And ("schedul*" or "planning")

And ("optimization*" or "optimisation*" or "*heuristic*")

And ("energy*" or "sustainab*" or "tariff*" or "*carbon*" or "*green*")

These keywords were selected so as to gather specifically energy-efficient manufacturing scheduling works. The search was conducted on the two most well established bibliographic databases: Web of Science™ and Scopus®. To avoid missing relevant papers due to varying authors' keyword choices, papers were also gathered through backward/forward reference search, including from the most recent review papers [Akbar and Irohara, 2018, Gao et al., 2020, Bansch et al., 2021, Para et al., 2022].

The literature search was performed in March 2022. In the first search (stage iii.) we collected 2179 and 2088 entries from the bibliographic databases Web of Science™ and Scopus®, respectively.

The data structuring and organizing stage involves several steps. We started by combining the two sets of results and removing the duplicated entries (through their Digital Object Identifier (DOI), title, or abstract similarity); after which we were left with 2820 papers. The first round of the screening process allowed for the exclusion of about 1050 papers by automatically eliminating papers out of the scope of this work, i.e., papers mentioning a form of "flow shop", "single machine", "parallel machine", "supply chain", or "logistic" in the title or abstract. In the second round of the screening, by reading the title and skimming the abstracts, we excluded about 1500 papers. Thus, at the end of stage iv. there were 270 records.

Then, based on these 270 works we performed backward and forward reference search (stage v.), added the records found to the 270 existing ones, removed duplicates and screened the newly found records by reading the title and skimming the abstracts (stage iv.), and repeated the process (stages iv. and v.) whenever new records were found. The number of papers that went through the final data structuring and organizing round, in which all papers were fully read, was 310. Before moving on to the final stage of the review process - bibliography classification and analysis - we excluded another 131 papers; therefore, we were left with 179 papers. Since seven of these papers are reviews, we ended up with 172

¹Note that although we considered the papers published in and after 2011, the first relevant papers were published in 2013.

papers to be further synthesized, analyzed, and reported on. This is almost four times the number of JSP and FJSP papers reviewed in the most recently published literature reviews [Gao et al., 2020, Bansch et al., 2021, Para et al., 2022]. Moreover, of these 172 papers, 115 have been published since 2019.

All papers are listed in a supplementary table attached to this paper. Although we have analyzed and synthesized all 172 papers to draw conclusions, we review and describe in detail a selected subset, which are among the most recent ones as well as among the most cited ones.

3 Literature analysis

The first works on energy-efficient scheduling problems date back to the 1990s Gahm et al. [2016], Gao et al. [2020], Akbar and Irohara [2018]. However, energy-efficient scheduling has only recently become the subject of systematic research. Figure 2.1 depicts the number of papers published, between 2013 and the first quarter of 2022, on the energy-efficient job shop problem and its variants (here and hereafter collectively designated as EEJSPs). As it can be seen, the number of publications has been growing quickly, particularly since 2018. Between 2013 and 2018 a total of 57 such papers were published while between 2019 and the first quarter of 2022 this number has gone up to 115 (more than doubling in half of the time).

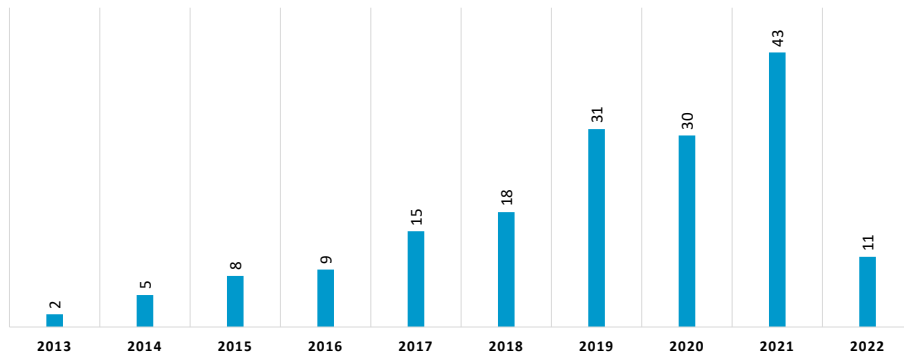


Figure 2.1: Number of publications, per year, on energy-efficient scheduling problems in job shop manufacturing systems. (Early view publications were assigned to 2022.)

The 172 papers have been published in 82 journals and two different books. However, only 15 journals have published three or more papers on EEJSPs. Overall, these 15 journals have published 89 papers, more than half of the papers found. Table 2.1 reports the list of journals and the number of papers published in each journal, whenever this number is at least 3.

Table 2.1: Publication source title with at least 3 papers published, between 2013 and 2022 (first quarter), on energy-efficient scheduling problems in job shop manufacturing systems.

Source title	# Publications
Journal of Cleaner Production	24
IEEE Access	12
Computers and Industrial Engineering	6
International Journal of Production Research	6
Sustainability (Switzerland)	6
Expert Systems with Applications	4
IEEE Transactions on Automation Science and Engineering	4
International Journal of Advanced Manufacturing Technology	4
PIMB, Part B: Journal of Engineering Manufacture	4
Swarm and Evolutionary Computation	4
Applied Soft Computing	3
International Journal of Production Economics	3
International Journal of Simulation Modelling	3
Journal of Intelligent & Fuzzy Systems	3
Mathematical Problems in Engineering	3

We have also analyzed the usage of keywords by extracting the author keywords, from each of the papers. The 32 most repeated keywords and the number of works that use them are depicted in Figure 2.2. (Please note that we have merged similar keywords and different versions of the same keyword, such as singular and plural and different spellings, usage of hyphenation, etc.) As expected “flexible job shop scheduling problem” and “job shop scheduling problem” are among the most used keywords, first and the third, respectively. Regarding energy efficiency scheduling, four different keywords are used in the literature, namely “energy-efficient scheduling”, “energy-saving scheduling”, “energy-aware scheduling”, and “energy-conscious scheduling”; the most common, by far, being “energy-efficient scheduling” (used more frequently than all other three combined). Three other keywords are used for this purpose, namely: “low carbon scheduling”, “green scheduling”, and “sustainable manufacturing”; however, they are mainly used in works concentrated on environmental and/or social objectives. The second most used keyword is “multi-objective optimization”, which is due to the fact that the most used approach to energy efficiency is considering two or more objectives. Among the objectives considered, the ones that are most frequently included as keywords are energy consumption and carbon emissions. Finally, several of the keywords refer to solution approaches.

Of the papers reviewed, 90 propose mathematical programming models; most being mixed-integer linear programming (MILP) models. There are, however, a few that propose constraint programming (CP) and dynamic programming (DP) models. The mathematical

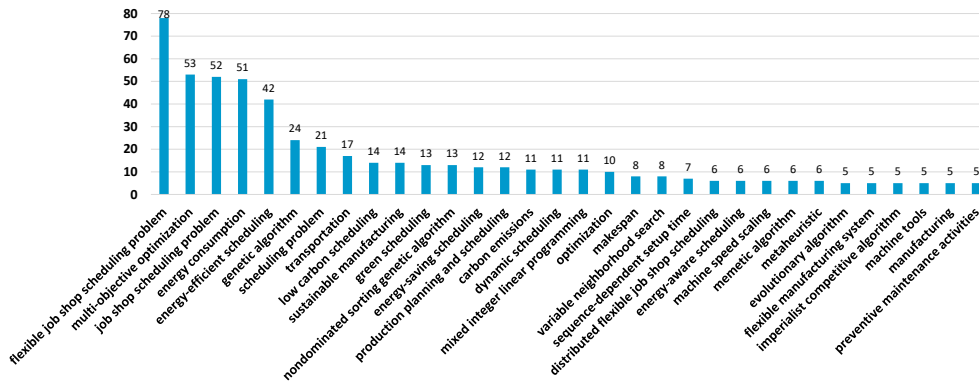


Figure 2.2: Keywords usage, whenever found in at least five works.

models have almost always been introduced just to formally define the problem. Hence, they have rarely been solved; even for small-sized problem instances [see, e.g., [Zhang et al., 2017b](#)]. Regarding the proposed solution approach, 149 of the papers reviewed propose at least one metaheuristic. This is not surprising as EEJSPs are NP-hard in the strong sense, for further details see Section 5.

The papers are classified according to six criteria: shop floor type, energy efficiency strategy, scheduling objectives, additional scheduling features, and (metaheuristic) solution approach, see Table 2.4. A full classification of the reviewed papers, extending the concise version given in Table 2.4, is provided as a supplementary spreadsheet table.

4 Features of the papers on EEJSPs

A job shop environment is characterized by having several machines that are used to process the operations of several jobs. Thus, each job must pass through, at least some of, these machines. To solve the JSP one needs to find the sequence of operations in each machine as well as the processing starting time of each operation. While in the JSP the job route, i.e., the sequence of machines that each job has to go through, is predefined; in the FJSP one also has to determine the machine in which each operation is processed on. Thus, one also has to determine the assignment of operations to machines.

Most of the papers reviewed (about two-thirds) consider a multi-objective version of the JSP or of the FJSP in which one of the objectives is energy related (typically, energy consumption, energy costs, carbon emissions, or peak power consumption). Thus, in these works solving the problem requires the usual decisions (job sequencing and operation start/completion time for the JSP and also job routing for the FJSP). Then, the goodness of a solution is evaluated by combining time and energy related performance measures. The remaining one-third also incorporates additional problem features that lead to additional

decision making variables, namely: machine status, whenever machines can be turned off; machine processing speed, whenever the processing speed can be chosen; and time slot allocation, whenever the scheduling horizon is divided into slots according to energy prices. This section classifies the papers reviewed in terms of the main features impacting the decision making process.

4.1 Shop floor

The shop floor type is the main feature when distinguishing problem type. This review only considers job shop environments. Nevertheless, whenever relevant, we clearly distinguish the JSP from the FJSP, since the latter encompasses the additional flexibility of choosing the machine that processes each operation. Therefore, there is more room to search for better strategies in what regards energy consumption. As illustrated in Figure 2.3, about two-thirds of the papers (113 out of 172) consider job routing flexibility. Additionally, it can also be seen that the number of papers on energy-efficient FJSP is growing faster than that of energy-efficient JSP, particularly in the most recent years. The main reasons for such a trend are likely to be i) the new advancements in manufacturing technology (also related to the development of Industry 4.0) and ii) the natural opportunities that the job routing choice provides regarding energy efficiency (different machines may have different characteristics, such as processing time, power consumption, etc.).

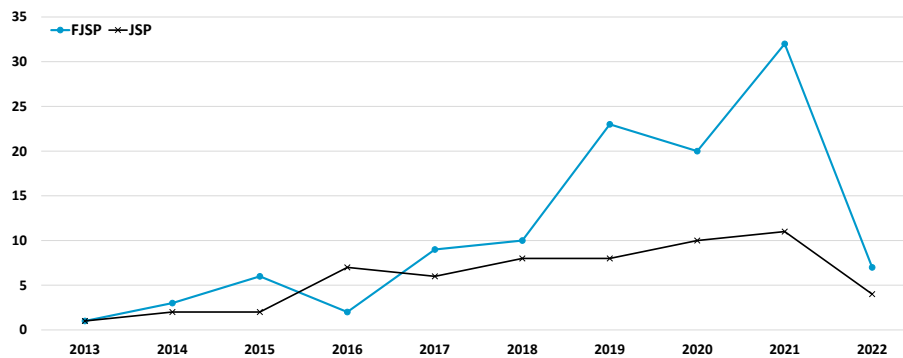


Figure 2.3: Number of publications, per year, addressing energy-efficient JSPs and FJSPs.

4.2 Strategies for energy efficiency

In the EEJSPs literature, three main strategies have been used to improve energy efficiency, namely: i) control machines working speed (speed adjustment), ii) schedule tasks under time-dependent energy prices (time of use, real time pricing, and critical peak pricing), and iii) switch machines to a power-saving mode while idle (e.g., turning them off). While under the first and the second strategies one needs to balance energy consumption and production

time (e.g., makespan, tardiness, and earliness) under the third strategy, energy savings from resorting to the use of a power-saving mode need to be balanced with energy requirements to restart and warm up the resources.

The first strategy acts on power consumption, which clearly impacts processing energy consumption. Additionally, it may also impact non-processing energy consumption as speeding up or slowing down a machine while processing an operation may reduce its idle time or the idle time of the machine processing the next operation of the corresponding job. Moreover, speeding up or slowing down a machine while processing an operation impacts the operation completion time, which in turn may impact the job completion time and even the completion time of the whole set of jobs (makespan).

In contrast, the third strategy addresses non-processing energy consumption only. The additional decisions of turning machines into a power-saving mode between consecutive operations result solely from whether the energy consumption during the idle time is larger than the one required for machine warming up. Such a strategy does not affect completion times.

The second strategy is related to energy supply characteristics, in particular its price. Scheduling under variable prices may have different impacts, depending on the chosen performance metric, i.e., objective function. For example, minimizing energy consumption and minimizing energy costs can lead to quite different schedules. A change in the consumption pattern by shifting electricity usage from a high cost period to a low cost period can lead to cost savings, even if the total energy consumption remains the same. This strategy needs to account for completion times, as shifting electricity usage implies delaying operation completion time.

Out of the 172 papers reviewed (59 on the JSP and 113 on the FJSP), 113 papers take energy efficiency into consideration just by including either an energy related objective function or energy related constraints. The remaining 59 papers incorporate at least one of the above-mentioned energy efficiency strategies. Indeed, six papers consider two such strategies simultaneously. Furthermore, energy efficiency strategies are more popular in works on the JSP than on the FJSP; they are considered in 31 JSP papers (53% of the 59 such papers) and in 28 FJSP papers (25% of the 113 such papers). This is most likely due to the FJSP energy saving built-in opportunities, see Section 4.1 for further details. Figure 2.4 summarizes these observations. Recall that six publications, one on the JSP and five on the FJSP, include two strategies each. Since we provided the number of publications incorporating each of the three strategies, these six papers are counted twice.

In the remaining of this subsection, we discuss only the 59 papers that incorporate energy efficiency strategies.

Several authors have resorted to the speed adjusting strategy; however, only machine processing speed (MS) has been considered [see, e.g., Zhang and Chiong, 2016, Lei et al.,

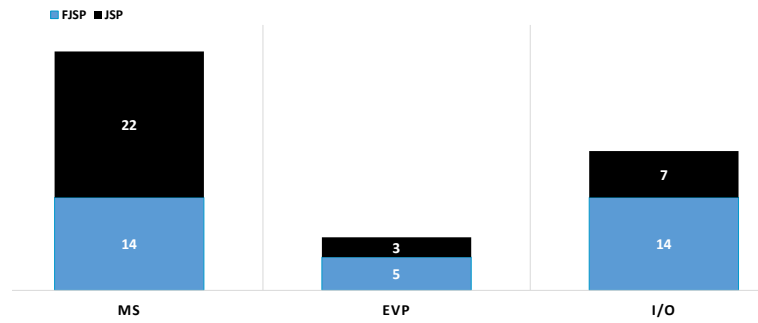


Figure 2.4: Number of JSP and FJSP publications incorporating energy-efficient strategies (MS - machine speed adjustment, I/O - turn-on and turn-off status, EVP - energy variable price).

2017, Wu and Sun, 2018, Salido et al., 2016b, He et al., 2021, Amelian et al., 2022, Applagate and Cook, 1991, Wei et al., 2022]. The exception being the work in [Homayouni, S.M. and Fontes, D.B.M.M., 2021] that considers simultaneously adjusting the machines processing speed and the vehicles traveling speed. By adjusting the working speed of some resources one may reduce energy consumption without impacting productivity. For example, non-critical resources (resources finishing their activities ahead of time) can perform some of their activities at a lower speed without impacting jobs completion time or makespan while reducing the energy consumption associated with those activities. Additionally, by reducing the processing speed of some activities, a reduction in the nonproductive energy consumption may also be accomplished since the idle time of those and/or other resources may be reduced. (Usually, performing activities at a lower speed requires a lower power demand and thus a lower energy consumption.) Machine speed adjustment stands out, by far, as the most used energy saving strategy. About 60% of the papers, addressing a JSP or a FJSP version extending its original scope, consider adjusting the machines processing speed (22 regarding the JSP and 14 the FJSP).

Electricity suppliers have been adopting time-varying pricing schemes to incentivize users to shift electricity consumption from high demand periods to lower demand ones; this way improving the reliability and efficiency of the electrical power grids as well as reducing carbon emissions in electricity generation. Therefore, a new trend in the research on EEJSPs, which optimizes energy costs by taking advantage of such incentives, has emerged [Zhang et al., 2017a, Hemmati Far et al., 2018, Gong et al., 2019]. Researchers, usually, resort to discrete time formulations that divide the scheduling horizon into time slots with equal duration, each having a predefined energy cost. Manufacturing activities are then allocated to and scheduled in these slots such that the total energy cost is minimized. However, under time-dependent energy prices lower energy costs may be accomplished by changing the demand pattern rather than by consuming less energy. Hence, researchers, typically, consider simultaneously a time related objective. This line of work is very recent and it has

been considered in only eight papers, three on the JSP and five on the FJSP.

The third strategy has been considered in 21 papers. Some of these papers include decisions on turning machines off while idle [e.g., [May et al., 2015](#), [Pach et al., 2014](#), [Zhang et al., 2017b](#), [Rakovitis et al., 2022](#), [Meng et al., 2019a](#), [Wu and Sun, 2018](#), [Liu et al., 2016](#), [Zhang et al., 2019b](#), [Caldeira et al., 2020](#)] and others on switching them to a stand-by mode [e.g., [Li et al., 2020c](#), [Wei et al., 2021](#), [Xu et al., 2022](#), [Li et al., 2020b](#)]. These works balance the energy saved from not having the machines running idle with that required to restart or warm up the machines, depending on whether the machines are switched off or switched to a power saving mode, respectively. In order to do so, most authors consider a switch on time and a switch on power consumption, which are then used to compute a switch on energy consumption [e.g., [Liu et al., 2014](#), [Wu and Sun, 2018](#), [Meng et al., 2019a](#), [Pach et al., 2014](#), [Zhang et al., 2017b](#)]. Some of these works even consider that the switch on time and power depend on whether the machine was previously on a standby mode or switched off [e.g., [May et al., 2015](#), [Li et al., 2020b](#)]. Other authors pre-calculate, for each machine, a break-even time period for which machine turn off and turn on is economically justifiable. Then, for each machine, whenever the time between two consecutive operations (i.e., the time between starting an operation and ending its immediate predecessor on the same machine) exceeds the break-even time the machine is switched off [e.g., [Liu et al., 2016](#), [Zhang et al., 2019b](#), [Caldeira et al., 2020](#)]. A few of these papers are more realistic as they also include machine transition states such as warming up and ramping down; often through the consideration of sequence-dependent setup times (SDST) [Gong et al. \[2019\]](#), [Garcia-Santiago et al. \[2015\]](#).

4.3 Energy efficiency objective functions

The most common approach to the EEJSPs is to solve the JSP or the FJSP while optimizing an energy related objective function. However, a few papers address energy efficiency concerns by imposing an upper limit on the total energy consumption [e.g., [Lei et al., 2018](#), [Tang and Dai, 2015](#), [Zhang et al., 2016](#), [Xu et al., 2016](#), [Xu and Wang, 2017](#)] or on the peak power consumption [e.g., [Kemmo et al., 2017](#), [Samukawa and Suwa, 2016](#), [Carlucci et al., 2021](#), [Masmoudi et al., 2019](#)]. Of the 172 papers reviewed, 163 consider energy related objective function(s). Although some of them also incorporate energy efficiency strategies, most find solutions to the original problem (JSP or FJSP) and then use an energy related performance measure to evaluate the quality of the solutions found (113 papers).

Overall, four different energy objective functions have been considered, namely: E - total energy consumption, EC - total energy cost, TC - total carbon emissions, and PP - peak power consumption. Most of these 163 papers, about two-thirds, minimize the total energy consumption. In contrast, just two papers [[Ichoua and Pechmann, 2014](#), [Gondran et al., 2020](#)] minimize the peak power consumption. The minimization of the total energy

cost and of the total carbon emissions have been considered more recently. Nevertheless, they already account for about 16% and 14% of the 163 papers, respectively.

To calculate the total energy consumption of the manufacturing system, researchers consider three to five types of consumption, namely: machine processing energy (P), machine idle energy (Id), machine setup energy (S), job transport energy (Tr), and indirect energy (In), energy associated with auxiliary equipment [Plitsos et al. \[2017\]](#), [Feng et al. \[2018\]](#), [An et al. \[2020\]](#), [Ren et al. \[2021\]](#), [Qu et al. \[2022\]](#), [Jiang et al. \[2022\]](#), coolant and lubricant [Wen et al., 2021](#), and keeping room temperature constant and lighting [Zhang et al. \[2017b\]](#), [Li et al. \[2020a\]](#).

The calculation of the energy consumption is very similar for the different types of consumption; mainly differing on the values used for the parameters. The mathematical expression for the total energy consumption, considering all five consumption types is provided in equation (2.1).

$$E = \sum_{m \in M} \sum_{j \in J_m} \left(p_{mj}^P t_{mj}^P + p_m^{Id} t_m^{Id} + p_{mj}^S t_{mj}^S \right) + \sum_{v \in V} \sum_{j \in J_v} \left(p^{Tr_e} t_j^{Tr_e} + p^{Tr_l} t_j^{Tr_l} \right) + p^{In} c_{max}. \quad (2.1)$$

Here, M is the set of machines; J_m is the set of operations to be processed on machine $m \in M$; p_{mj}^P , p_m^{Id} , and p_{mj}^S are, respectively, the power consumption of machine m when processing operation j , when idle, and when being setup for operation j and t_{mj}^P , t_m^{Id} , and t_{mj}^S are the corresponding times. The energy required to transport the job to have operation j processed includes the empty travel energy to pickup the job (from the position where the vehicle finished its last task to the position where the job previous operation was processed) and the loaded travel energy to deliver the job to where operation j is to be processed. Thus, $t_j^{Tr_e}$ and $t_j^{Tr_l}$ are, respectively, the empty and loaded travel times associated with operation j and p^{Tr_e} and p^{Tr_l} are the vehicles' power requirements when traveling empty and loaded, respectively. We assume that the vehicles are equipped with automatic start-stop technology, thus there is no consumption while idle. (Note that, usually, all vehicles have the same power requirements, which do not depend on the job being transported.) The indirect power consumption p^{In} is constant throughout the completion time of all jobs C_{max} .

The calculation of the energy costs as well as the calculation of the carbon emissions is, typically, based on the total energy consumed, as given in equations (2.2) and (2.3), where λ_{co} and λ_c are, respectively, the coefficients that convert the consumed energy into carbon emissions and monetary units.

$$EC = \lambda_c E, \quad (2.2)$$

$$TC = \lambda_{co} E. \quad (2.3)$$

Regarding peak power consumption, the two works that minimized it do not provide any mathematical expression for PP . However, it should be as given in Equation 2.4, or at least similar, since it calculates the maximum instantaneous power consumption considering all five types of consumption.

$$PP = \max_{t \leq C_{max}} \left\{ \sum_{m \in M} \sum_{j \in J_m} \left(p_{mj}^P x_{mj}^t + p_m^{Id} y_m^t + p_{mj}^S z_{mj}^t \right) + \sum_{v \in V} \left(p^{Tr_e} u_v^{Tr_e} + p^{Tr_l} w_v^{Tr_l} \right) + p^{In} \right\}. \quad (2.4)$$

Here, x_{mj}^t , y_m^t , and z_{mj}^t are binary variables that take the value 1 if at time t machine m is processing operation j , is idle, and is being setup to process operation j , respectively, and zero otherwise. Similarly, $u_v^{Tr_e}$ and $w_v^{Tr_l}$ are binary variables that take the value 1 if at time t vehicle v is traveling loaded and empty, respectively, and zero otherwise. (Recall that we are assuming the vehicles to be equipped with automatic start-stop technology.)

Figure 2.5 shows the classification of the 161 papers addressing EEJSPs by optimizing energy related objective functions regarding: the objective function considered (E , EC , and TC), the problem addressed (JSP and FJSP), and the type of energy consumption included (P , Id , S , Tr , and In). (Note that most authors consider just some of the energy consumption types.) The papers on peak power consumption are excluded from this figure since there are only two [Ichoua and Pechmann \[2014\]](#), [Gondran et al. \[2020\]](#) and both consider only processing energy consumption. Figure 2.5 has three circles: the most inner circle depicts, in parenthesis, the number of papers considering each of the energy efficiency objective functions; the middle circle shows the number of papers on the JSP and on the FJSP for each of the objectives considered in the inner circle; and the outer circle depicts the percentage of papers that considers each of the energy consumption types for each problem type (middle circle) and each objective function (inner circle). Note that since several papers consider more than one energy consumption type, the total percentage value for each category is greater than 100% and that the percentages refer to the 161 papers being analyzed in this subsection.

As it can be seen in Figure 2.5, almost all works consider machine processing energy (P). Its minimization is mainly tackled through speed adjustment in JSPs [e.g., [Zhang and Chiong, 2016](#), [Salido et al., 2016b, 2017](#), [Jiang et al., 2018b](#), [Lu et al., 2021b](#)] and through job routing in FJSPs [e.g., [He et al., 2015](#), [Mokhtari and Hasani, 2017](#), [Piroozfard et al., 2018](#), [Wang et al., 2018a](#), [Dai et al., 2019](#), [Lei et al., 2018](#), [Gong et al., 2018](#), [Dai et al., 2015](#), [Lei and Guo, 2015](#), [Zhang et al., 2015](#), [Jiang and Deng, 2018](#)].

The second most commonly considered energy consumption type is machine idle energy, that is, the energy consumed by machines when they are running idle or when they are switched to a standby mode [[Zhang and Chiong, 2016](#), [Liu et al., 2014](#), [May et al., 2015](#), [He et al., 2015](#), [Lei et al., 2017](#), [Wu and Sun, 2018](#)]. Quite often, machines having idle

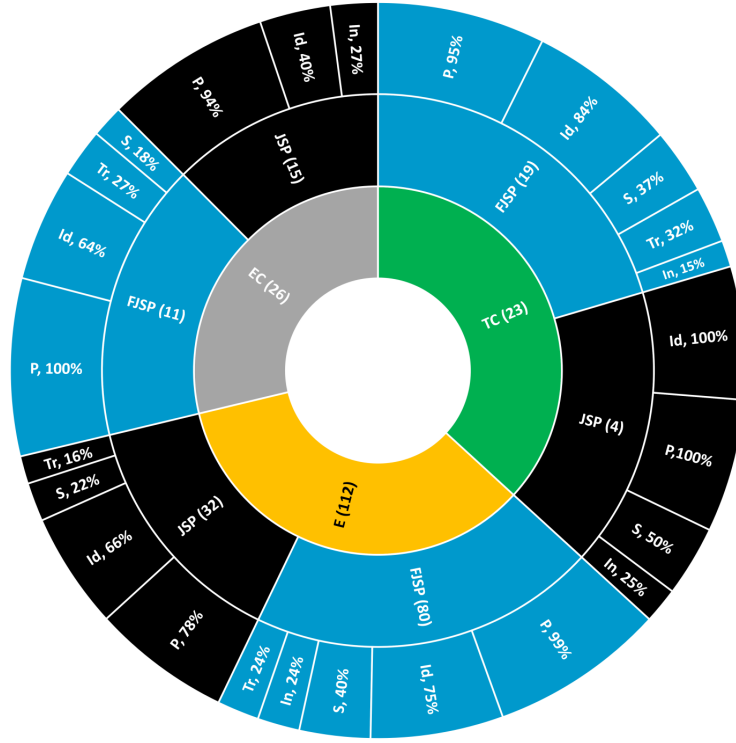


Figure 2.5: Paper classification regarding energy efficiency objective functions and their components for JSPs and FSJPs. (The areas are not to scale.)

times between consecutive operations are not turned off. On the one hand, frequently turning machines on and off leads to additional degradation. On the other hand, some machines require a non-negligible setup time and/or cost when turned back on.

Setup energy is quite often disregarded as, typically, setup times are either disregarded or accounted for in the operation processing times. However, some studies consider setup times explicitly as well as the associated energy consumption [Gong et al., 2019, Garcia-Santiago et al., 2015, He et al., 2021]. Additionally, some authors consider that setup energy consumption (S) includes not only the energy required to exchange tools and machine settings between consecutive operations but also the energy required to change the state of the machines (e.g., warming up and ramping down) [May et al., 2015, Wu and Sun, 2018, Liu et al., 2016, Dai et al., 2019].

The energy required to transport the jobs around the shop floor is also accounted for by six papers addressing the JSP and by 28 papers addressing the FJSP. However, since no limitation and/or scheduling decisions are considered, job transport time is equivalent to sequence-dependent setup time and thus, the job transport energy could be considered as setup energy [e.g., Zhang et al., 2015, Dai et al., 2019, Han et al., 2021, Li and Lei, 2021, Zhang et al., 2021, Ebrahimi et al., 2020, An et al., 2020]. Nevertheless, there are a few exceptions. Some authors [Far et al., 2019, Wang et al., 2021a, Barak et al., 2021,

Li et al., 2021a, Hemmati Far et al., 2018, Li et al., 2021b, Zhou and Lei, 2021, Li et al., 2022, Zhang et al., 2021] schedule transport and take into account the energy required to load/unload vehicles and others [Jiang et al., 2020, Du et al., 2021, Xu et al., 2021b, Meng et al., 2020, Liu et al., 2021, Luo et al., 2020b] consider the energy required to transport the jobs between geographically distributed facilities.

Finally, the least considered energy consumption type is the indirect energy, which is usually due to auxiliary equipment [e.g., Dai et al., 2015, Zhang et al., 2017b, Jiang et al., 2018b, Meng et al., 2019b]. Some works consider the indirect energy consumption to be proportional to the makespan and thus, a single objective function is used to minimize the makespan and the energy consumption [e.g., Zhang et al., 2019a, Feng et al., 2018, Jiang et al., 2022].

Figure 2.6 depicts a year-wise evolution of the number of papers that consider each of the five energy consumption types. It is clear that the number of publications considering energy consumption has been growing significantly. In particular, the number of papers considering the energy consumed by the transport resources has grown quite impressively; the number of such studies published in 2021 is almost the same as those published over the previous four years. In contrast, the number of papers considering indirect energy consumption has recently been decreasing.

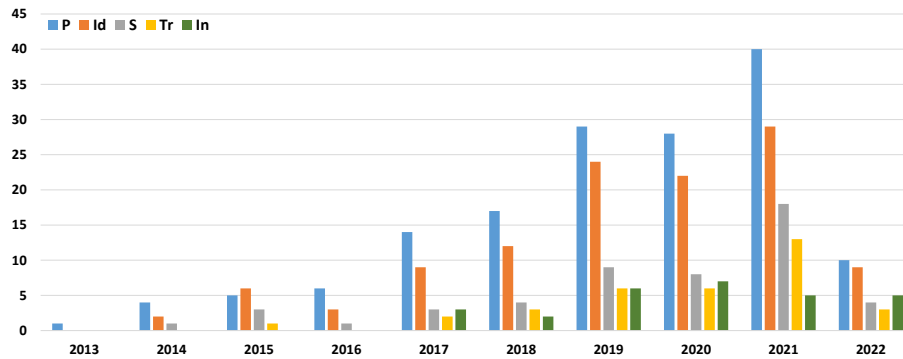


Figure 2.6: Number of papers published, per year, that include each of the five energy consumption types.

4.4 Other objective functions

About 81% of the reviewed papers include more than one objective function; thus, addressing a multi-objective version of the problem. The objective functions considered include an energy efficiency objective function and, at least, one additional objective function. The latter being, typically, related to performance objectives (e.g., makespan, earliness, or tardiness) and/or to economic objectives (e.g., production costs).

The makespan (C_{max}) is the time required to complete all operations of all jobs and is the most frequently considered objective function. In fact, it is optimized in about 64% of the reviewed papers [e.g., [May et al., 2015](#), [He et al., 2015](#), [Wu and Sun, 2018](#), [Yin et al., 2017b](#), [Salido et al., 2016b](#)]. A closely related objective that some times is considered is the total processing time, which is given by the sum, over all jobs and all operations, of the operation processing time [e.g., [Mokhtari and Hasani, 2017](#), [Coca et al., 2019](#)].

The second most frequently considered objective is the tardiness, which measures the difference between the job due date and the job completion time. About 20% of the reviewed papers optimize some form of tardiness, namely: total tardiness (T) [e.g., [Piroozfard et al., 2018](#), [Lei et al., 2018](#), [Jiang et al., 2018a](#), [Luo et al., 2020a](#), [Pan et al., 2021](#)], total weighted tardiness (wT) [e.g., [Zhang and Chiong, 2016](#), [Liu et al., 2014, 2016](#), [Zhang et al., 2016](#), [Abedi et al., 2020](#)], total weighted tardiness and earliness (wTE) [[Wei et al., 2021](#), [Ichoua and Pechmann, 2014](#), [Liu et al., 2021](#)], tardiness cost (T_{cost}) [[Ebrahimi et al., 2020](#), [Ayyoubzadeh et al., 2021](#)], mean tardiness ($\bar{T}$) [[Xu et al., 2021a](#)], and maximum tardiness (T_{max}) [[Li et al., 2019](#), [Ahangar et al., 2021](#)].

Regarding economic objectives, the most frequently considered one is the total production cost (PC), which is optimized in about 13% of the studies. The costs accounted for include costs with human resources [[Li et al., 2021c](#), [Zhu et al., 2020](#), [Gong et al., 2019, 2018](#)], raw materials [[Ning and Huang, 2021](#), [An et al., 2020](#)], maintenance [[An et al., 2020](#), [Liao and Wang, 2018](#)], transportation [[Barak et al., 2021](#)], and processing [Liu et al. \[2021\]](#), [Jiang et al. \[2019\]](#), [Lu and Jiang \[2019\]](#). Other economic objectives include penalty costs associated with earliness and/or tardiness [[Liu et al., 2021](#), [Ayyoubzadeh et al., 2021](#), [Xu et al., 2016](#)], machine under and over-utilization [Hemmati Far et al. \[2018\]](#), and customer dissatisfaction [[Liao and Wang, 2019](#)].

Besides the performance and economy objectives, a few other objectives have been considered, although in just a very small number of papers. These include machine performance goals such as machines workload (ML) [[Lei et al., 2017](#), [Zhang et al., 2015](#), [Gong et al., 2019](#)], rescheduling disruption (RD) [[Luo et al., 2020a](#), [Caldeira et al., 2020](#)], machines' fault probability (FP) [[Sui et al., 2021](#)], and system reliability (Rel) [[Amelian et al., 2022](#), [Mokhtari and Hasani, 2017](#)]; product related goals such as work in process (WIP) [[Zhang et al., 2015](#)], raw material usage (RM) [[Xu and Wang, 2017](#)], quality and defective rate (Q) [[Jiang et al., 2014](#), [Xu et al., 2016](#)], and customer satisfaction (CuS) [[Gong et al., 2019](#)]; and social objectives included mainly through working conditions such as noise level (N) [[Yin et al., 2017b,a](#), [Coca et al., 2019](#)], ergonomic risk (Erg) [[Hongyu and Xiuli, 2021](#)], and vibration (Vib) [[Coca et al., 2019](#)].

Although some works include simultaneously environmental (energy), economic (makespan), and social (noise) objectives, not many do so. This is further discussed in Section 5.4 and can be observed in Table 2.2.

4.5 Additional scheduling problems

As seen, most of the reviewed papers address the EEJSP by just including additional objectives. Thus, the problem being solved is still the JSP or the FJSP. Nevertheless, energy-efficient solutions are obtained as the objective functions include at least one energy metric. In contrast, some works extend the scope of the addressed problem by considering additional problem features that require additional decision making. We have already discussed the works that do so by adjusting machine speed, by switching the machine status, or by considering time slots with different prices. Here, we discuss works that include, simultaneously, decisions on other resources or other activities.

Problems scheduling simultaneously machines and workers consider several workers with different skills. Additionally, due to the complexity of the machines, each worker can only operate a subset of the existing machines. Furthermore, each operation may require different worker skills, thus not all workers can perform all operations. Finally, each operation can only be processed on a subset of the existing machines. Therefore, when scheduling an operation one has to look for an available machine among the ones that can process the operation and also for an available worker that can perform the operation and can operate the chosen machine. Although workers do not impose energy consumption, they may impose constraints on the operations schedule, which in turn may lead to a higher energy consumption. Such problems have been addressed while minimizing processing energy consumption [Gong et al., 2018, Lei and Guo, 2015, Peng et al., 2021, Hongyu and Xiuli, 2021] and while minimizing carbon emissions [Zhu et al., 2020].

Another line of research considers problems in which both the machines that process the operations and the vehicles that transport the jobs have to be scheduled simultaneously. The transportation imposes on its own additional energy requirements, as vehicles need to move around the shop floor. Additionally, transportation may also lead to a larger energy consuming schedule due to the required synchronization of machines and vehicles [Far et al., 2019, Wang et al., 2021a, Du et al., 2021, Barak et al., 2021, Li et al., 2021b]. The vast majority of the studies either disregards transportation or considers that transport time is included in the processing time; consequently, a job can be processed on the next machine immediately after its completion on the previous one. Others assume a transport time between the machines and also that the job can be transported immediately after the completion of the operation. Such assumption implies the existence of an unlimited number of vehicles, which is unrealistic. Energy consumption associated with transportation cannot be ignored and it can be optimized by a proper scheduling scheme.

The performance of machines degrades, naturally, as a result of aging and wear, which leads to a decrease in performance (quality and speed) and reliability (faults and failures). Thus, some authors consider preventive maintenance, which has to be scheduled together with the manufacturing operations [Mokhtari and Hasani, 2017, Abedi et al., 2020, An

et al., 2020, Wang et al., 2021a]. The purpose of such integration is twofold: to maintain the performance of machines at an acceptable level, this way also reducing the energy consumption, and to minimize the energy consumed by maintenance activities.

Other subproblems that impact the total energy consumption have been considered, although less frequently: layout optimization (LOP) [Ebrahimi et al. [2020], Li et al. [2021a]] - machine location (and reallocation) is determined at the same time that the manufacturing operations are scheduled; job process planning (JPP) [Dai et al., 2015] - job routing is chosen from a set of predefined job routes; and batch scheduling (BS) [Garcia-Santiago et al., 2015] - machines are setup to process a batch of similar operations; distributed manufacturing scheduling (DMS) [Luo et al. [2020b], Du et al. [2021], Jiang et al. [2020], Lu et al. [2021a], Fathollahi-Fard et al. [2021]] - operations may be processed on machines that are located in different factories, which are geographically distributed. Among these, we distinguish the latter two works since they address non-identical factories and consider the three pillars of sustainability (economic, social, and environmental); thus, complying with the triple bottom line principle.

5 Solution approaches

Energy-efficient job shop problems are NP-hard in the strong sense since they extend a well-known NP-hard problem, the JSP [Garey et al., 1976]. Thus, exact methods may not be able to obtain an optimal solution within a reasonable amount of (computation) time. Additionally, they may not even be able to find a feasible solution, particularly in the presence of problem instances of a realistic size. Therefore, the majority of the studies propose approximate solution methods that are capable of finding good quality solutions quickly, but do not ensure optimality.

The solution approaches proposed include heuristics, metaheuristics, and hybrid metaheuristics. While heuristics exploit problem-dependent information to find a good solution to a specific problem, metaheuristics are general algorithms that can be applied to a broad range of problems.

5.1 Heuristic methods

Heuristic methods are designed for a specific problem and take advantage of the problem characteristics as well as of previous experience with the problem. They are capable of finding feasible solutions very quickly, which, often, are reasonably good. Hence, heuristics may be used on their own to find feasible solutions quickly; this is particularly relevant in the presence of a very short time-frame or deadline. On the other hand, they may be used

together with or embedded in other optimization algorithms. Metaheuristic approaches, frequently, resort to heuristics to generate initial solutions and/or to try to improve the solutions they found. The latter results in hybrid metaheuristics, see Subsection 5.3.

In the papers reviewed, heuristics have been proposed for dynamic EEJSPs as these involve finding schedules in real-time in response to uncertainties in customer demand, resource availability, energy disruptions, among others. Quite often researchers designate such approaches as real-time reactive scheduling. The progress in the Internet of Manufacturing Things (IoMT) is facilitating the availability of information, particularly in real-time; hence, dynamic scheduling (DS) has, recently, been capturing more research attention. About 14% of the papers reviewed propose DS approaches, which were implemented by resorting to heuristic methods (five papers were published until 2018 and 19 in and after 2019). DS has been implemented by using two main strategies to react to real-time events: full schedule reconstruction [Zhang et al., 2016] and specific schedule changes addressing only the disrupted resources and impacted tasks [e.g., Caldeira et al., 2020, Li et al., 2022, Nouri et al., 2020, Zhou et al., 2022].

For example, in [Nouri et al., 2020] a reactive heuristic is used to identify the disrupted resources (machines or vehicles) and to reassign the impacted tasks. The authors reassign each impacted task to the (possible) resource that cumulatively satisfies: i) smallest operating time or earliest completion time, ii) lowest energy consumption, and iii) smallest slack time and highest energy consumption during idle time. Another reactive heuristic is proposed in [Caldeira et al., 2020]. In this case, the need for dynamic scheduling is due to the arrival of new jobs. Whenever a new job arrives, its operations are tentatively inserted into the machines idle time, shifting the previously assigned operations to a later time if necessary and possible without compromising the makespan; otherwise they are sequenced as the last tasks of the machines.

An alternative and interesting approach to deal with uncertainty is to model it explicitly by resorting, for example, to fuzzy numbers. Fuzzy arithmetic is a powerful tool to introduce uncertainty into mathematical models. Some of the reviewed papers, not many, use triangular fuzzy numbers to model uncertainty regarding processing times [Pan et al., 2021, Afsar et al., 2022, González-Rodríguez et al., 2020] and setup times and defective product rate [Far et al., 2019]. On the other hand, in [Shi et al.] the uncertainty associated with delivery times is modeled through trapezoidal fuzzy numbers. A recent discussion on sources of uncertainty in scheduling can be found in Yuan et al. [2022]; although for a different problem. They propose a multi-attribute fuzzy decision-making approach to the disassembly scheduling problem under uncertainty. This problem has a relevant impact on the environment since it allows to obtain parts or sub-assemblies from end-of-life products.

Several of the metaheuristics proposed, see Subsection 5.2, resort to a heuristic to obtain initial solutions rather than generating them randomly. Recall that metaheuristics are

general purpose algorithms and do not take advantage of the problem characteristics. Thus, having good initial solutions, typically, enhances their performance. Many authors, have used heuristics, mainly constructive heuristics, to obtain initial solution(s). For example, [Jiang et al., 2018b] proposes a whale optimization algorithm (WOA) for the JSP with speed adjustable machines. An initial population of solutions is obtained by combining some randomly generated solutions with solutions obtained by dispatch rules. The latter being randomly selected from the following four: i) schedule (the first available operation of) the job with the largest remaining processing time, ii) schedule (the first available operation of) the job with the most operations remaining, iii) schedule (the first available operation of) the job with the shortest total processing time, and iv) schedule (the first available operation of) the job with the longest total processing time. The processing speed is always randomly assigned to the each operation.

5.2 Metaheuristics

Metaheuristics are high-level iterative processes that guide the search over the solution space. They may consider a single solution or a collection of solutions (population of solutions). Single solution metaheuristics are trajectory based while multiple solution ones can mainly be divided into evolutionary-based and nature-inspired; the latter being sometimes categorized as bio-inspired (e.g., ant colony optimization), human-based (e.g., imperialistic competitive algorithm), swarm-based (e.g., particle swarm optimization), physics/chemistry-based (e.g., electromagnetism), and others less known and less used categories. The search process is stochastic in nature and its efficiency and effectiveness are closely related to a trade-off between exploitation (intensive search of a promising area) and exploration (wide search of the solution space in the search of new areas).

Single solution metaheuristics iteratively modify a single candidate solution in the hope of finding a better solution in its neighborhood. Thus, this type of algorithms is exploitation oriented and can get trapped into a local optimum. However, they are all enhancements of the basic local search procedure since they are probabilistic in nature. On the one hand, the modification to apply to the candidate solution is probabilistic and, on the other hand, worse candidate solutions are sometimes accepted. Simulated annealing (SA) [Kirkpatrick et al., 1983], one of the most well-known single solution metaheuristics, borrows concepts from the physical annealing of metals. To find a new solution, SA moves in the search space by taking steps of a random but constrained size from the candidate solution. If the new solution is better than the candidate one, then it replaces the candidate one. A worse solution is probabilistically accepted; the acceptance probability is a function of how long the algorithm has been run for and of how much worse the new solution is. Other well-known single-solution metaheuristics are iterated local search (ILS) [Lourenço et al., 2003],

variable neighborhood search (VNS) [Mladenović and Hansen, 1997], and Tabu search (TS) [Glover, 1989].

Over the years many evolutionary-based metaheuristics have been proposed. One of the most popular and well performing being Genetic algorithms (GAs) [Goldberg and Holland, 1988]. A GA evolves a population of solutions along several generations through natural selection and genetics. Solutions are randomly selected for reproduction in order to produce offspring (new solutions), which inherit the characteristics of the parents. The offspring are then added to the next generation. Although the selection is random, following on Darwin's theory of natural evolution, better solutions are given higher probability of being chosen for reproduction. By doing so, the characteristics of good solutions are more likely to be preserved as new solutions are obtained by coping the genes of the parents. A crossover operator is used to defined which genes are inherited from which parent. Additionally, some solutions are changed through mutation in order to maintain diversity and prevent premature convergence.

Nature-inspired metaheuristics search the solution space by imitating natural phenomena such as the behavior and interaction in bird flocking, fish schooling, foraging bees, flower pollination, etc. Many such algorithms have been proposed and used in a variety of applications. The literature on this type of metaheuristics is rapidly expanding. One of the most popular nature-inspired metaheuristics is particle swarm optimization (PSO) [Kennedy and Eberhart, 1995], which was originally devised for continuous optimization problems. PSO works with a collection of solutions, termed particles, that are moved around the search space by changing the position and velocity of each particle. The movement of each particle is influenced by its own experience (its best previous position) and the experience of its neighbors (the best previous position in the neighborhood). This way moving the swarm toward the best solutions.

Metaheuristics are proposed in 149 of the 172 reviewed papers. Evolutionary-based metaheuristics are the most popular as 64% of the papers propose them; followed by nature-inspired metaheuristics that are proposed in 29% of the papers. Single-solution metaheuristics are proposed in 7% of the papers.

Overall, the papers reviewed propose 38 different metaheuristics to find solutions to EEJSPs. Although in some papers more than one metaheuristic is implemented, we only count one metaheuristic per paper - the one proposed and described in detail.

Figure 2.7 shows the metaheuristics proposed as well as the number of papers proposing each one of them, whenever two or more papers do so. Genetic algorithms are by far the most used metaheuristic; over 53% of the proposed metaheuristics are GAs. Additionally, there are over 13 times more papers proposing GAs than papers proposing imperialistic competitive algorithms, the second most proposed approach.

Hybrid metaheuristics have also been proposed for EEJSPs and they are discussed next.

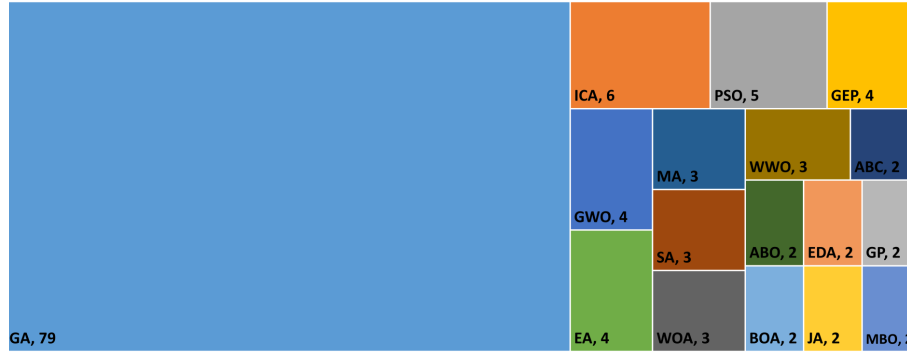


Figure 2.7: Metaheuristics proposed for EEJSPs and number of papers proposing them, whenever proposed by two or more papers. (The list of abbreviations provides the full name of every algorithm.)

5.3 Hybrid metaheuristics

Over the years many metaheuristic algorithms combining various algorithmic components have been reported. Such algorithms are commonly referred to as hybrid metaheuristics. The main motivation behind the hybridization of different algorithms is to exploit the complementary character of different optimization strategies, thus taking advantage of their synergies. In fact, the hybridization of metaheuristics is a widespread practice, especially in what concerns the use of local search methods within population-based metaheuristics; regardless of being evolutionary-based or nature-inspired. Metaheuristics, although good at exploring the search space and identifying areas with high quality solutions, are usually less effective at exploiting the accumulated search experience, that is, at finding the best solutions within these high quality areas. Therefore, local search is used to refine the solutions that are generated during the search process as its strength is the capability of quickly searching the vicinity of a given solution.

Hybrid metaheuristics are proposed in almost 17% of the reviewed papers; the most common being the hybridization of GAs and local search procedures. For example, [Zhang and Chiong \[2016\]](#) embed an ILS procedure within a multi-objective GA (moGA) to minimize wT and E in a JSP with speed adjustable machines. The GA evolves the population of solutions through the usual genetic operators and at each generation the ILS attempts to improve the generation best solutions by searching for better ones in their neighborhood using three different strategies. At each generation the solutions are partitioned into a series of Pareto ranks and then solutions in each rank are sorted. Let set B consist of the solutions in the top half and let wT_m and E_m be, respectively, the median values of wT and E of the solutions in set B . Set B is partitioned in four subsets, namely: B_1 that consists of the solutions with wT at least as good as the median value and E worse than the median value, i.e., $wT \leq wT_m$ and $E > E_m$; B_2 that consists of the solutions with $wT > wT_m$ and

$E \leq E_m$; B_3 that consists of the solutions with $wT \leq wT_m$ and $E \leq E_m$; and B_4 that consists of the solutions with $wT > wT_m$ and $E > E_m$. Then, the neighborhood of the solutions in subset B_1 (biased toward wT) is explored through a heuristic in which the sequence of a pair of operations on a critical machine are swapped while their processing speeds remain unchanged. To attempt to improve the solutions in subset B_2 (biased toward E) the processing speed of non-critical operations is decreased. The two heuristics are applied sequentially to the solutions in subset B_3 and no local search is applied to the solutions in subset B_4 . A similar idea is pursued in [Zhang et al., 2015] that divides the population into four subsets, each associated with the best solutions regarding each of the four objective functions considered, and attempts to find better solutions in each subset by improving the corresponding objective. In [Kurniawan et al., 2021] two local search strategies are used: one to change the operations starting time to cheaper periods (under EVP prices) and another to insert a random operation of a tardy job into an earlier position.

Similar strategies have been proposed in Mokhtari and Hasani [2017] for the FJSP, in [Wu and Sun, 2018, Wei et al., 2022] for the FJSP with speed adjustable machines, and in [Jiang et al., 2020] for the JSP with speed adjustable machines. In all of them a GA is used to find and rank feasible solutions and to evolve the populations. Then, at each generation the neighborhood of the best solutions is searched for in an attempt to find better solutions. While Mokhtari and Hasani [2017] resorts to an SA algorithm that randomly selects an operation to be reinserted at a random position and randomly swaps the selected elements of two operations; [Wu and Sun, 2018] reassigns critical operations (operations of a last completed job) to machines that can process them sooner and slows down non-critical operations as long as the makespan remains unaffected; and [Jiang et al., 2020] swaps two operations on a critical machine (a last finishing machine), increases the processing speed of a randomly selected critical operation, and decreases the processing speed of a randomly selected operation of a first complete job. A different strategy for hybridizing local search is proposed in [Lei et al., 2018], which hybridizes an ICA and a VNS algorithm. Since in the problem they address an energy upper limit is imposed, generating feasible solutions can be quite time consuming. Therefore, the ICA finds good solutions while disregarding the energy upper limit, i.e., solutions with good makespan values that may be infeasible regarding the energy limit. The VNS is then used to search for solutions that comply with the energy upper limit, in the neighborhood of the set of non-dominated solutions.

Dai et al. [2019] propose a different approach to hybridize a GA, a PSO, and an SA as the PSO and the SA are used within and as a replacement of the genetic operators, respectively. The GA crossover operator uses the PSO information-sharing mechanism to generate offspring that inherit some genes from the best global solution and the remaining ones from the parents. The mutation operator is replaced by a simulated annealing algorithm. Other examples include hybridizing GA and PSO [Wang et al., 2018a, Ren et al., 2021], PSO and

Table 2.2: Number of papers considering multi-objective functions combining non-energy related functions ($\text{Obj}_{\text{other}}$) with energy related functions (Obj_{EE}), whenever at least three papers do so.

$\text{Obj}_{\text{other}}$	Obj_{EE}		
	E	EC	TC
$C_{\max}$	45	2	6
wT	6	2	
PC	3	5	
$C_{\max}; T$	5		1
$C_{\max}; ML$	3		3
$C_{\max}; PC$	3		1
$C_{\max}; N$	3		
$C_{\max}; RD$	2		1
$C_{\max}; PC; Q$	2		1
T_{cost}		3	
T		1	2

SA [Ebrahimi et al. \[2020\]](#), and GA and TS [[Xu et al., 2021b](#)], among others.

5.4 Multi-objective algorithms

In single-objective optimization we seek to find an optimal solution and the superiority of a solution over other solutions is easily determined by comparing their objective function values. In contrast, in multi-objective optimization we are looking for a set of solutions (rather than just one). These solutions define the best trade-offs between conflicting objectives. The goodness of a solution is determined by the concept of dominance. A solution dominates another solution if it is strictly better in at least one objective, not being worse in any of the remaining objectives. Ideally, we would like to find the Pareto-optimal set, that is, all solutions of the entire feasible decision space that are non-dominated. Usually, however, that is not possible. Thus, the objective becomes to find a set of diverse solutions that approximate the Pareto-optimal front, which is the boundary defined by the Pareto-optimal set.

From the 172 papers reviewed, 139 consider a multi-objective version of the problem tackled. The number of objective functions considered ranges from two to five. However, most papers consider either two or three. The most common multi-objective problem versions consider the minimization of the total energy consumption E and of the makespan $C_{\max}$ (about 32% of the papers). Nevertheless, other combinations of objective functions have been considered. Table 2.2 reports the combinations of objective functions used in multi-objective approaches as well as how many papers used each one, whenever a combination is used in three or more papers.

Some of the objectives reported in Table 2.2 are used in just two or three papers, each calculating them in a different way. Hence, readers wishing to find out more on how they are calculated are referred to those works: *ML* - machines workload [Lei et al., 2017, Zhang et al., 2015, Gong et al., 2019], *RD* - rescheduling disruption [Luo et al., 2020a, Caldeira et al., 2020], *Q* - quality and defective rate [Jiang et al., 2014, Xu et al., 2016], and *N* - noise level [Yin et al., 2017b,a, Coca et al., 2019]. The mathematical expressions for the other objectives are provided in equations (2.5) to (2.9). (Here only the new notation is defined; for the remaining notation see Section 4.3.)

$$c_{max} \geq c_j, \forall j \in J \text{ where } c_j \text{ is the completion time of job } j, \quad (2.5)$$

$$T = \sum_{j \in J} T_j, \text{ where } T_j \geq (c_j - d_j)^+ \text{ and } d_j \text{ is the due date of job } j, \quad (2.6)$$

$$wT = \sum_{j \in J} w_j T_j, \text{ where } w_j \text{ is the weight of job } j, \quad (2.7)$$

$$T_{cost} = \sum_{j \in J} \lambda_j T_j, \text{ where } \lambda_j \text{ is a penalty cost associated with the tardiness of job } j, \quad (2.8)$$

$$PC = \sum_{m \in M} \sum_{j \in J_m} (\lambda_{mj}^P t_{mj}^P + \lambda_m^{Id} t_m^{Id}) + \sum_{v \in V} \sum_{j \in J_v} \lambda_v^{Tr} t_j^{Tr} + \sum_{j \in J} \lambda_j^{RM} + \sum_{l \in L} \lambda_l^c + \sum_{a \in MA} \lambda_a^{ma}, \quad (2.9)$$

where λ_{mj}^P and λ_m^{Id} are, respectively, the cost of machine m when processing operation j and when idle; λ_v^{Tr} is the operational cost of vehicle v and t_j^{Tr} is the travel time required by job j ; λ_j^{RM} is the cost of the raw material required to produce job j ; L is the set of human resources and λ_l^c is the cost associated with collaborator l ; and MA is the set of maintenance activities and λ_a^{ma} is the costs associated with maintenance activity a .

Over 94% of the solution approaches proposed for multi-objective EEJSPs are meta-heuristic. The remaining ones propose game theory [Zhang et al. [2017c], Wang et al. [2020, 2021b], simulation [Pach et al. [2014], Cai et al. [2022], Raileanu et al. [2017], Gupta and Jain [2021], Wang [2019], multi-agent systems [Wang et al. [2018b], constraint programming [Salido et al. [2016a], Escamilla et al. [2016], MIP-based heuristics [Giglio et al. [2017], Hassani et al. [2019], and deep learning methods [Zhou et al. [2022].

Over the years many methods have been proposed to approximate the Pareto front. Some of these methods scalarize the objectives and obtain a single objective function by adding the objective functions, usually, pre-multiplied by a weight. An optimal solution to this single objective problem is Pareto optimal to the multi-objective problem. An approximation of the Pareto front is obtained by solving a series of single objective problems, with different weights. Although such a strategy is simple and easy to implement, it does have some major drawbacks. On the one hand, it cannot be ensured that the chosen weights produce a Pareto-optimal solution in a desired region of the objective space. On the other hand, two different sets of weights may not produce two different Pareto-optimal solutions. Hence, a uniformly distributed set of Pareto-optimal solutions cannot be ensured. Addition-

ally, if the objective space is non-convex, then some Pareto-optimal solutions will not be found.

Almost 36% of the proposed multi-objective (MO) metaheuristics use a scalarized objective function obtained by the sum, the weighted sum, or the normalized weighted sum of the original objective functions [e.g., [He et al., 2015](#), [Mokhtari and Hasani, 2017](#), [Yin et al., 2017b](#), [Salido et al., 2016b](#), [Piroozfard et al., 2018](#), [Wang et al., 2018a](#), [Liu et al., 2019](#), [Salido et al., 2017](#), [Yin et al., 2017a](#)]. Other methods of finding Pareto solutions resorting to single objective problems include the analytical hierarchy process (AHP) method, in which the weights are determined by the decision maker [Xu et al. \[2021b\]](#) and the lexicographic method [[Lei and Guo, 2015](#), [Plitsos et al., 2017](#)], in which the objectives are considered one at a time in the order of importance given by the decision maker. Thus, in the lexicographic method, the problem is solved for the most important objective and then for the second most important objective with an additional constraint imposing the previously attained value for the first objective and so on until all objectives have been considered or just one optimal solution exists.

Solution approaches considering all objectives simultaneously but independently have become the current trend and among this evolutionary algorithms have been taking the lead. This is not a surprise since they have the advantage of dealing with a set of possible solutions (the so-called population), which allows to find several solutions of the Pareto optimal set in a single “run” of the algorithm (instead of having to perform a series of separate runs). The most commonly proposed multi-objective evolutionary algorithms (MOEAs) are variants of the NSGA-II proposed in [Deb et al. \[2002\]](#). NSGA-II uses an explicit diversity-preserving strategy together with an elite-preservation strategy that are implemented by: i) classifying the solutions into a number of mutually exclusive equivalent non-dominated sets (NDS); ii) determining the crowding distance (CD) of the solutions in each NDS, which is given by half of the perimeter of the enclosing cuboid with the nearest neighboring solutions in the same front; and iii) selecting solutions by a crowding tournament in which a solution wins if it has a better rank or a better crowding distance if they have the same rank. Some of the approaches proposed just rank the solutions, typically using the non-dominated sets [see, e.g., [Lei et al., 2017](#), [Liu et al., 2017](#), [Jiang et al., 2020](#)]; however, most approaches also use CD to sort the solutions with the same rank [see, e.g., [Liu et al., 2014](#), [May et al., 2015](#), [Wu and Sun, 2018](#), [Liu et al., 2016](#), [Zhang et al., 2015](#), [Jiang et al., 2014](#), [Zhang et al., 2019b](#), [Yang et al., 2016](#)]. Other metaheuristics resorting to NDS and CD include ICA [Peng et al. \[2021\]](#), PSO [[Barak et al., 2021](#)], and GWO [[Luo et al., 2019](#)].

There are, however, other sorting mechanisms. For example, [Deb and Jain \[2013\]](#) resort to the reference point direction (RPD) and [May et al. \[2015\]](#) to the density estimator (Dens). In the RPD, solutions in the direction of a larger number of reference points (ideally provided by the decision maker) are better while in the Dens, the goodness of the solutions

is provided by the summation of the Euclidean distance between the solution and all other solutions with the same rank. The combination of NDS and RPD procedures is mainly used in NSGA-III [see, e.g., [Gong et al., 2019](#), [Coca et al., 2019](#), [Sun et al., 2021](#), [Hongyu and Xiuli, 2021](#)] and in ICA [[Li et al., 2019](#), [Li and Lei, 2021](#)].

Figure 2.8 summarizes the methods used to address multi-objective EEJSPs as well as the mechanisms used to rank and sort solutions when addressing all objectives independently but simultaneously.

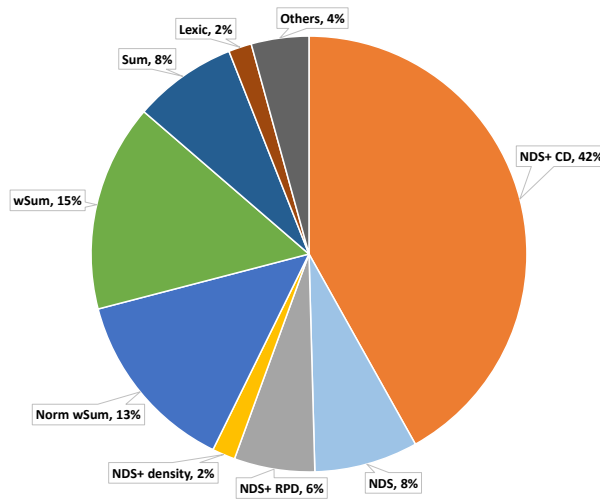


Figure 2.8: Multi-objective solution methods: Ranking and sorting mechanisms for evaluating solutions under multiple objectives and scalarization methods to convert the several objectives into a single one (Sum - summation, wSum - weighted sum, Norm wSum - normalized wSum, Lexic - lexicographic).

After finding a final set of solutions, the quality of the solutions has to be evaluated and whenever possible compared with the Pareto Front. Although several performance metrics have been proposed over the years, the solutions to EEJSPs have rarely been evaluated or compared by resorting to such metrics. To the best of our knowledge, just 13 papers report such evaluations. The metrics used include the generational distance (GD) and inverted generational distance (IGD) that measure the convergence of the solutions to a reference Pareto front [[Dai et al., 2019](#), [Luo et al., 2019](#), [Abedi et al., 2020](#), [Zhu et al., 2020](#), [Sun et al., 2021](#), [Pan et al., 2021](#)], the hyper volume (HV) that measures the size of the dominated space according to some reference points [[Abedi et al., 2020](#), [An et al., 2020](#), [Ren et al., 2021](#), [Li et al., 2021c](#), [He et al., 2021](#)], and the spread that evaluates the diversity and uniformity of the solutions [[Luo et al., 2019](#), [Abedi et al., 2020](#), [He et al., 2021](#), [Sun et al., 2021](#)]. One possible reason behind the very small number of papers reporting such metrics may be the lack of reference solutions. This problem can be obviated if researchers use the same problem instances in their computational experiments. The existence and availability

of (benchmark) problem instances are discussed next.

6 Problem instances and data sets

The quality of the solutions obtained by metaheuristic approaches can only be analyzed or inferred by comparing the solutions they found with either optimal solutions or the solutions found by other approaches. Optimal solutions are, usually, not available. A few mathematical models were proposed for EEJSPs; however, most were not solved. On the one hand, EEJSPs are NP-hard problems and thus, only small-sized instances may be solved to optimality. On the other hand, the multi-objective nature of EEJSPs increases problem complexity, as it requires solving the models several times in order to approximate the Pareto Front.

Comparisons with the results of previous works can seldom be found. The main reasons being the incompatibility and unavailability of the data used for testing, since authors use problem instances that are either randomly generated, randomly adapted from instances of closely related problems, or specific case-studies. Additionally, authors, typically, do not make publicly available the problem instances they use. Hence, the comparison of a newly proposed (meta)heuristic with previously proposed ones, requires the implementation of all of them as well as to perform computational experiments with all (meta)heuristics on the same set of problem instances. This is no easy task. First, some authors do not provide all details of the methods they propose. Second, since there are some differences in the definition of the addressed problems, the approaches would have to be adapted so that all could solve the same problem. Third, since no previous comparison between the proposed methods exists, there is no information on which one(s) to select, i.e., on the best performing ones. Finally, the computational burden quickly becomes prohibitive. Therefore, no comparisons are, usually, reported.

One simple step that can be taken to help remedy the lack of comparisons is to “force” authors to make publicly available the data of the instances they consider; less than half of the reviewed papers do so. Also, in addition to the value of the objective functions, authors should report the computational effort. Another important step would be to create a library of such problem instances together with the best known solutions (schedule and value of the objective functions). This would be a manageable and relatively simple task if all authors contribute with the data and solutions of the instances used. We have started such a process and urge researchers to contribute.

We have created a web Library (EEJSP Library²) and have already uploaded some data sets that can be used as benchmark problem instances in future studies. In our selection, we consider the problem instances for which the full data set is provided either in the

²<https://fastmanufacturingproject.wordpress.com/eejsp-library/>

corresponding paper or in an online database. We strongly encourage authors to provide additional data sets and corresponding solutions; for example, by contacting us.

The problem instances being used in the literature include case studies, randomly generated instances, as well as instances adapting well-known benchmark problem instances previously proposed for other related problems. However, just a minority of the reviewed papers, 41 out the 172 reviewed, features adapted benchmark instances. Several authors introduce and discuss specific case studies on problems that can be cast as energy-efficient (flexible) job shop problems. The problem instances associated with such studies involve the FJSP [Wang et al. \[2018a\]](#), [Jiang et al. \[2014\]](#), [Zhang et al. \[2019b\]](#), the FJSP and tool allocation [\[He et al., 2015\]](#), the FJSP and WoS [\[Gong et al., 2018\]](#), the FJSP with TrT [Liu et al. \[2019\]](#), [Dai et al. \[2019\]](#), [Liu et al. \[2017\]](#), the FJSP with LOP and TrS [Li et al. \[2021a\]](#), the DS FJSP [Ayyoubzadeh et al. \[2021\]](#), and the JSP with TrT [Liao and Wang \[2019\]](#).

Random problem instances have been proposed for energy-efficient (flexible) job shop problems. Below, we list the problems they have been proposed for as well as the works proposing them: FJSP [Yin et al. \[2017b\]](#), FJSP including I/O machine status [Rakovitis et al. \[2022\]](#), FJSP with TrT [Dai et al. \[2019\]](#), FJSP with TrS [Li et al. \[2021b\]](#), FJSP considering DS [Caldeira et al. \[2020\]](#), DS FJSP [Dai et al. \[2015\]](#), JSP [Yin et al. \[2017a\]](#), [Xu et al. \[2022\]](#), JSP with TrT [Xu and Wang \[2017\]](#), and JSP and MaS [Amelian et al. \[2022\]](#).

Regarding adapted energy-efficient JSP instances, they have been adapted, mainly, from the JSP instances originally proposed by [Adams et al. \[1988\]](#) (abz5~abz9), [Fisher and Thompson \[1963\]](#) (ft06, ft10, and ft20), [Lawrence \[1984\]](#) (la01~la40), and [Applegate and Cook \[1991\]](#) (orb01~orb10). Different authors adapted them in different ways and by adding additional data, typically randomly generated: [Gondran et al. \[2020\]](#) energy consumption for each operation, [Zhang and Chiong \[2016\]](#), [Salido et al. \[2016b\]](#), [Jiang et al. \[2018b, 2019\]](#), [He et al. \[2021\]](#) energy consumption for each operation at different speed levels, [May et al. \[2015\]](#), [Liu et al. \[2016, 2014\]](#) energy consumption for each operation and for turn on-off actions, [Abedi et al. \[2020\]](#) energy consumption for each operation and each maintenance activity and a due date for each job, and [Zhang and Chiong \[2016\]](#) energy consumption for each operation at different speed levels and a due date for each job.

Finally, the FJSP instances commonly adapted are those originally proposed by [Brandimarte \[1993\]](#) (mk01~15), [Dauzère-Pérès and Paulli \[1997\]](#) (dp1~18), [Kacem et al. \[2002\]](#) (Kacem), and [Hurink et al. \[1994\]](#) (Hurink). To adapt them, additional parameters have to be considered: [Lei et al. \[2017\]](#), [Xu et al. \[2016\]](#), [Wu and Sun \[2018\]](#), [Li and Lei \[2021\]](#) generate energy consumption for each operation at different speed levels, [Zhang et al. \[2017b\]](#) generates energy consumption for each operation and for turn on-off actions, [Zhang et al. \[2015\]](#) generates energy consumption for each operation and for transport tasks, [Luo et al. \[2020b\]](#), [Liu et al. \[2021\]](#) generate energy consumption for each operation and DMS data,

and [Lei and Guo \[2015\]](#) generates energy consumption for each operation and workers' capabilities data.

Table 2.3 summarizes the benchmark instances considered and already included in EE-JSP Library. This table has six columns: the first one (Ref.) provides the paper reference, the second and third columns provide, respectively, the energy efficiency objective function (Obj_{EE}) and additional objective function(s) if considered (Obj_{other}). The next two columns report the energy efficiency strategy (EE strategy) used (refer to Section 4.2) and the additional scheduling problems (Features) considered (refer to Section 4.5). Lastly, the problem instances column provides information on the origin of the instances considered (original instance when adapted, "App" when based on a real-world application, and "Rnd Ins" when randomly generated).

As said earlier, not many works can be found that compare the results they obtain with the results of previous works. Additionally, most of the works reporting comparisons do so just for some features as the problem definitions and/or objective functions are not exactly the same. For example, [Abedi et al. \[2020\]](#) compare their results with those of [Essafi et al. \[2008\]](#) and [Salido et al. \[2016b\]](#). However, there is no direct comparison between Pareto fronts with either of the two works, as they do not share the same combination of objective functions. Instead, the comparison addresses a single objective function at a time, with each work: the total weighted tardiness is compared with that of [Essafi et al. \[2008\]](#) and the energy consumption is compared with that of [Salido et al. \[2016b\]](#). As far as we know, the only exceptions are the works reported in [Salido et al. \[2016a\]](#), [Escamilla et al. \[2016\]](#), [Salido et al. \[2016b\]](#). The first two compare the Pareto fronts, regarding trade-offs between makespan and energy consumption, obtained by a moGA and a CP model for four sets of problem instances. The authors extend the previous work by incorporating a local search algorithm into the moGA; this way improving its performance [[Salido et al., 2016b](#)].

7 Conclusions

Metaheuristics have been used to find high-quality solutions to a large number of complex problems in a wide range of application areas (e.g., manufacturing scheduling, molecular modeling, inventory allocation, project scheduling, maritime operations, network flows, and many others). The scientific community has shown them to be a viable, and often superior, alternative to more traditional (exact) methods, in particular when tackling combinatorial optimization problems. Moreover, metaheuristics are more flexible than more traditional (exact) methods since they are problem independent and thus, can be adapted to fit the needs of almost any real-life optimization problem. Additionally, they can be used to find a "good enough" solution in a computation time that is "small enough". However, metaheuristics are not able to ensure the optimality of the solutions they find. On the contrary, exact methods

Table 2.3: Benchmark problem instances for EEJSPs.

Ref.	Obj _{EE}	Obj _{other}	EE strategy	Features	Problem instances
JSP					
[Zhang et al., 2016]	E	$C_{max}; wT$		DS	ft06
[Salido et al., 2016b]	E	C_{max}	MS		Rnd Ins
[Yin et al., 2017a]	E	$C_{max}; N$	MS		Rnd Ins
[Xu and Wang, 2017]	E	C_{max}		TrT	Rnd Ins
[He et al., 2021]	E	$C_{max}; T$	MS	SDST	orb1~3; abz7~abz9; la26~28; la31~33
[May et al., 2015]	E	C_{max}	I/O		ft06, 10, 20
[Liu et al., 2014, 2016]	E	wT	I/O		ft10
[Zhang and Chiong, 2016]	E	wT	MS		Rnd Ins
[Abedi et al., 2020]	E	wT	MS	MaS	Rnd Ins
[Jiang et al., 2018b]	EC		MS		la01~35; ft6, 10, 20
[Jiang et al., 2019]	EC	PC	MS		ft06, 10, 20; la01~la40
[Xu et al., 2022]	EC		TOU; I/O		Rnd Ins
Liao and Wang [2019]	EC	$PC; CuS$		TrT	App
Amelian et al. [2022]	EC	$TE; Rel$	MS	MaS	Rnd Ins
[Gondran et al., 2020]	PP	C_{max}			la01~40
FJSP					
Wang et al. [2018a]	E	PC			App
Zhang et al. [2019b]	E	C_{max}			App
Jiang et al. [2014]	E	$C_{max}; PC; Q$			App
[Yin et al., 2017b]	E	$C_{max}; N$			Rnd Ins; App
[Xu et al., 2016]	E	$C_{max}; PC; Q; RM$			Kacem
[Caldeira et al., 2020]	E	C_{max}, RD	I/O	DS	Rnd Ins
[Wu and Sun, 2018]	E	$C_{max}, \# I/O$	MS; I/O		mk01~10
Li et al. [2021b]	E	C_{max}		TrS	Rnd Ins
[Dai et al., 2019]	E	C_{max}		TrT	Rnd Ins; App
Liu et al. [2019]	E	C_{max}		TrT	App
[Luo et al., 2020b]	E	C_{max}, ML_{max}		DMS; TrT	Hurink
[Lei et al., 2017]	E	ML	MS		mk01~13; dp1~18
Li and Lei [2021]	E	C_{max}, T	MS	SDST; TrT	mk01~15; dp1~18
Li et al. [2021a]	E	C_{max}		LOP; TrS	App
[Zhang et al., 2017b]	E		I/O		Hurink; Rnd Ins
[Rakovitis et al., 2022]	E		I/O		Rnd Ins
He et al. [2015]	E	C_{max}		Tools	App
[Dai et al., 2015]	E	C_{max}		JPP	Rnd Ins
Gong et al. [2018]	E	C_{max}, LC		WoS	App
[Lei and Guo, 2015]	E	C_{max}		WoS	mk01~12; dp1~12
Liu et al. [2017]	TC	C_{max}		TrT	App
[Zhang et al., 2015]	TC	$C_{max}; ML; WIP$		TrT	Kacem
[Liu et al., 2021]	TC	$PC; C_{max}; TE$		DMS; TrT; SDST	Kacem
Ayyoubzadeh et al. [2021]	EC	T_{cost}		DS	App

can, theoretically, ensure optimality if allowed to run long enough. Nevertheless, often they are not able to find an optimal solution in a reasonable amount of time; many times not even a feasible one.

This work reviews metaheuristic approaches proposed, in the last decade, for the energy-efficient job shop scheduling problem and its variants (EEJSPs). EEJSPs are NP-Hard as they are extensions of the JSP, which has been proven NP-Hard. A further complexity associated with EEJSPs arises from the fact that energy efficiency is usually optimized along with other objective function(s), such as makespan, tardiness, production costs, etc. Since frequently conflicting objective functions are considered, one no longer looks for an optimal solution, which may not even exist. Instead, we look for a set of solutions that defines the best trade-offs between the conflicting objectives, i.e., a set of non-dominated solutions. Metaheuristics are particularly suited to address this type of problems as most of them evolve a set of candidate solutions, rather than a single solution.

Manufacturing systems often employ several resource types, such as workers, machines, and vehicles. In such systems, usually, two or more resource types collaborate to perform the activities. Therefore, resources should be scheduled simultaneously. Although research on JSPs integrating more than one resource type has been reported in the literature, integrated EEJSPs are yet to be addressed. This is a very important avenue of research since the impact of scheduling collaborative resources separately is even more relevant in EEJSPs. For example, consider a manufacturing environment in which the jobs need to be transported around the shop floor. In addition to the direct increase in energy consumption required by the transport vehicles, machines may have longer idle times as they may have to wait for the delivery of jobs and vehicles may also have idle times as they may have to wait for the completion of operations. Thus, impacting not only productivity, resource utilization, completion time, and production costs, but also energy consumption. Other examples include preventing maintenance activities, which need to be scheduled at the same time as manufacturing activities.

Many technological developments have been achieved over the years. Regarding manufacturing systems, the most recent such developments lead to the existence of intelligent manufacturing systems - Industry 4.0. Industry 4.0, also called the Internet of Manufacturing Things, is closely tied with the digitalization of industrial processes and equipment, cyber-physical systems, and the capability of gathering and processing in real-time data and information. Once the extracted data and information are transformed into useful knowledge by resorting to, e.g., machine learning methods, it can be used to improve the efficiency and quality of the scheduling solutions. Future research is needed in, at least, two different directions, namely: i) how to transform the data and information collected into knowledge and ii) how to use the collected information and derived knowledge to improve the efficiency and quality of the scheduling solutions. Regarding the former, the main issues that

need further research are the communication and cooperation of the different types of data sources, i.e., how to handle the increasing variety of smart components and equipment and how to integrate the information coming from different sources in a consistent and homogeneous way. Regarding the latter, the information obtained and the knowledge derived can be used to increase scheduling efficiency and robustness. The better and more reliable information available can be used, on the one hand, to predict changes in the system, e.g., resource breakdowns, energy disruption, worker's fatigue, etc, and on the other hand, to adapt the existing schedules to cope with such changes.

One way of taking advantage of the information and produced knowledge (i.e., information on unexpected events and predictions) is to reschedule the activities ensuring feasibility; this way, producing more robust and effective schedules. (The need for rescheduling can also come from considering the arrival of new jobs during the planning horizon.)

Another way of adapting to such events is to control the resources in real-time; for example, adjusting the speed of some of the resources. Moreover, resource control in real-time may also be used to improve energy efficiency: slowing down resources that would complete their tasks ahead of time or switching resources to a standby mode in the presence of increased idle times.

Another interesting direction is to directly address the uncertainty regarding, e.g., processing times, energy supply, energy consumption, availability of resources, etc. This involves the development of new optimization tools such as robust optimization, simheuristics, stochastic models, fuzzy logic, among others. Robust optimization methods, typically, optimize the worst possible outcomes considering solutions that are feasible, regardless of data and uncertain parameters. Simheuristics add a simulation layer to the metaheuristics that allows the optimization component to deal with scenarios under uncertainty. Stochastic models optimize the problem in several stages based on the current known state of the system and correct the decisions at successive stages, once more reliable data becomes available. Fuzzy logic creates an approximation mechanism to incorporate the uncertainties into other optimization tools (e.g., exact methods and metaheuristics). Although these solution approaches are particularly relevant for EEJSPs; they have been rarely proposed.

The incorporation of new problem characteristics, such as the ones discussed above leads to new problem versions that are even more complex. Hence, new faster and more robust approaches are of the uttermost importance.

Almost all papers reviewed consider simultaneously economic and energy objective functions. Only a few consider the three pillars of sustainability (economic, environmental, and social). For example, three papers consider the makespan (economic objective), total energy consumption (energy objective), and noise (social objective). Given the small presence of the social pillar in the papers reviewed and the growing importance of the subject, research on jobs shop problems also including social objectives is identified as a main future

research topic.

Despite the fact that the number of studies solving EEJSPs is growing fast, specifically in the past three years, the number of cross references is quite low. According to the data extracted from Scopus® in March 2022, the H-index for EEJSP papers is 35; however, only six papers published in and after 2019 are among the top 35 highly cited papers. This may be a sign that the EEJSPs' research community is not fully aware of the rich literature on EEJSPs, specifically of those published in the most recent years.

A large number of papers is covered in this review paper, yet it may miss some relevant and important studies. However, not all data are precisely recorded in the two data bases used in this work. Additionally, we have disregarded studies that have been published in conference proceedings. Finally, some of the papers may use different terminology or may describe the problem and/or the solution approaches in a different way and thus may not have been found through our searches.

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Data Availability: The publications reviewed in this work and their classified data are available as a supplementary Excel table.

Conflicts of Interest: The authors declare no conflict of interest.

8 Appendix

Table 2.4: Classification of the papers cited.

Ref	floor	Obj _{EE}	P	Id	S	T	In	Obj _{other}	MO App	Sol App	EE strategy	Features
2022												
Li et al. [2022]	FJSP	<i>E</i>	✓	✓		✓	✓	C_{max}	wSum	Learn+ GP		TrS; DS
Amelian et al. [2022]	JSP	<i>EC</i>	✓					TE ; Rel	NDS+ CD	NSGAII+Simul	MS	MaS
Xu et al. [2022]	JSP	<i>EC</i>	✓	✓	✓		✓			FA	EVP; I/O	
Rakovitis et al. [2022]	FJSP	<i>E</i>	✓	✓	✓		✓			GEP	I/O	
Qu et al. [2022]	FJSP	<i>E</i>	✓	✓	✓		✓	C_{max} ; PC		EMA		
Jiang et al. [2022]	FJSP	<i>E</i>	✓	✓		✓	✓			AMO		
Wei et al. [2022]	FJSP	<i>E</i>	✓	✓	✓			C_{max}	NDS+ CD	NSGAII	MS	
Zhou et al. [2022]	FJSP	<i>TC</i>	✓	✓				C_{max} ; RD		Ensemble deep forest		DS
Cai et al. [2022]	JSP	<i>E</i>	✓			✓		CuS ; $Util$	Norm wSum	Simul		DS
Pan et al. [2021]	JSP	<i>E</i>	✓	✓				C_{max} ; T	NDS	moGA		
Afsar et al. [2022]	JSP	<i>E</i>		✓				C_{max}	NDS+ CD	NSGAII		
2021												
He et al. [2021]	JSP	<i>E</i>	✓	✓	✓			C_{max} ; T	Fuzzy RPD	GA	MS	SDST
Sun et al. [2021]	FJSP	<i>TC</i>	✓	✓				C_{max} ; ML	NDS+ RPD	NSGAIII		
Li et al. [2021a]	FJSP	<i>E</i>	✓	✓	✓	✓	✓	C_{max}	NDS+ CD	NSGAII		LOP; TrS
Barak et al. [2021]	FJSP	E ; EC	✓					PC	NDS+ CD	moPSO		TrS
Du et al. [2021]	FJSP	<i>E</i>	✓	✓		✓		C_{max}		EDA+VNS		DMS; TrS
Wang et al. [2021a]	FJSP	<i>E</i>	✓			✓		C_{max}	NDS+ CD	GA+DEA		MaS; TrS
Peng et al. [2021]	FJSP	<i>E</i>	✓	✓	✓		✓	C_{max} ; N	NDS+ CD	ICA		WoS; TrT
Xu et al. [2021b]	FJSP	<i>TC</i>	✓	✓		✓		C_{max} ; PC ; Q	Fuzzy AHP	GA+TS		DMS; TrT
Wei et al. [2021]	JSP	<i>E</i>	✓	✓	✓			C_{max} ; wTE	NDS+ RPD	NSGAIII	I/O	
Lu et al. [2021b]	JSP	<i>E</i>	✓	✓				C_{max}	NDS+ CD	MA	MS	
Ning and Huang [2021]	FJSP	<i>TC</i>	✓					C_{max} ; PC	NDS+ CD	NSGAII+QEA		
Liu et al. [2021]	FJSP	<i>TC</i>	✓	✓	✓	✓		PC ; C_{max} ; TE	NDS+ Dens	moGA		DMS; TrT; SDST
Ayyoubzadeh et al. [2021]	FJSP	<i>EC</i>	✓	✓				T_{cost}	NDS+ CD	NSGAII		DS
Ahangar et al. [2021]	FJSP	<i>E</i>	✓	✓				C_{max} ; T_{max}	NDS+ CD	NSGAII	MS	
Li et al. [2021c]	JSP	<i>E</i>	✓	✓	✓			C_{max} ; T ; LC	Fuzzy RPD	moEA	MS	WoS
Kurniawan et al. [2021]	JSP	<i>EC</i>	✓					wT	NDS+ CD	NSGAII	EVP	
Li and Lei [2021]	FJSP	<i>E</i>	✓	✓	✓	✓		C_{max} ; T	NDS	ICA	MS	SDST; TrT
Hongyu and Xiuli [2021]	FJSP	<i>E</i>	✓	✓				C_{max} ; Erg	NDS+ RPD	NSGAIII		WoS
Han et al. [2021]	FJSP	<i>E</i>	✓			✓		C_{max} ; PC	NDS+ CD	NSGA-II+VNS		TrT
Zhang et al. [2021]	FJSP	<i>E</i>	✓	✓	✓	✓		C_{max}	NDS+ CD	NSGA-II+LS		TrT
Li et al. [2021b]	FJSP	<i>E</i>	✓			✓		C_{max}	wSum	SA		TrS
Carlucci et al. [2021]	JSP		✓					C_{max}		MIP	MS	
Wen et al. [2021]	FJSP	<i>TC</i>	✓	✓	✓	✓		C_{max} ; T	NDS+ CD	NSGA-II		JPP
Zhou and Lei [2021]	JSP	<i>E</i>	✓	✓		✓		C_{max}	NDS	GWO		TrS
Sui et al. [2021]	FJSP	<i>E</i>	✓					C_{max} ; FP	NDS+ CD	NSGA-II		
Ren et al. [2021]	FJSP	<i>E</i>	✓	✓	✓		✓	C_{max}	NDS	PSO+GA		
Xu et al. [2021a]	FJSP	<i>E</i>	✓	✓				$\bar{T}$	NDS+ CD	GP		DS
Wang et al. [2021b]	FJSP	<i>E</i>	✓	✓	✓			C_{max} ; ML_{max}		Game theory		DS; DMS
Gupta and Jain [2021]	JSP	<i>E</i>	✓	✓				C_{max} ; $\bar{T}$		Simul		DS; MaS; SDST
2020												
Jiang et al. [2020]	JSP	<i>E</i>	✓	✓				C_{max}	NDS	moEA	MS	DMS
Abedi et al. [2020]	JSP	<i>E</i>	✓					wT	NDS+ CD	MA	MS	MaS
Luo et al. [2020b]	FJSP	<i>E</i>	✓			✓		C_{max} ; ML_{max}	NDS+ CD	NSGAII		DMS; TrT
Luo et al. [2020a]	JSP	<i>EC</i>	✓					T ; RD	Norm wSum	GA	MS	DS
Caldeira et al. [2020]	FJSP	<i>E</i>	✓	✓	✓			C_{max} ; RD	NDS+ CD	BSA	I/O	DS
Nouri et al. [2020]	FJSP	<i>E</i>	✓	✓				C_{max}	wSum	PSO		DS
Ebrahimi et al. [2020]	FJSP	<i>EC</i>	✓			✓		T_{cost}	Sum	PSO+LS; PSO+SA		LOP; TrT
Li et al. [2020c]	FJSP	<i>E</i>	✓	✓				C_{max}	NDS+ CD	NSGAII	I/O	DS
An et al. [2020]	FJSP	<i>E</i>	✓	✓	✓	✓	✓	C_{max} ; T ; PC	NDS+ CD	NSGAII		MaS; TrT
Zhu et al. [2020]	FJSP	<i>TC</i>	✓	✓				C_{max} ; LC	NDS+ CD	MA		WoS
Gondran et al. [2020]	JSP	<i>PP</i>	✓					C_{max}	NDS+ CD	NSGAII		
Li et al. [2020a]	FJSP	<i>E</i>	✓	✓	✓		✓			MBO		WoS
Meng et al. [2020]	FJSP	<i>E</i>	✓	✓			✓			SFLA		DMS
Wang et al. [2020]	FJSP	<i>E</i>	✓	✓			✓	C_{max} ; ML	wSum	Game theory		DS; JPP
Li et al. [2020b]	FJSP	<i>TC</i>	✓	✓	✓			C_{max} ; ML	NDS+ CD	ABC	MS; I/O	
Shi et al.	FJSP	<i>E</i>	✓	✓	✓			C_{max} ; CuS		GA+AIA		
González-Rodríguez et al. [2020]	JSP	<i>E</i>		✓				wT	NDS+ CD	NSGAII		
2019												
Dai et al. [2019]	FJSP	<i>E</i>	✓	✓	✓	✓		C_{max}	NDS+ CD	GA+SA+PSO		TrT
Lei et al. [2018]	FJSP		✓	✓				C_{max} ; T	NDS+ CD	ICA+VNS		
Liu et al. [2019]	FJSP	<i>E</i>	✓			✓		C_{max}	wSum	GA+GSO		TrT
Luo et al. [2019]	FJSP	<i>E</i>	✓	✓				C_{max}	NDS+ CD	GWO	MS	
Gong et al. [2019]	FJSP	<i>EC</i>	✓	✓	✓			C_{max} ; LC ; ML	NDS+ RPD	NSGAIII	I/O; EVP	WoS; SDST
Jiang et al. [2019]	JSP	<i>EC</i>	✓	✓				PC	Sum	WOA	MS	
Lu and Jiang [2019]	JSP	<i>EC</i>	✓					PC	Sum	Bat	MS	
Coca et al. [2019]	FJSP	<i>TC</i>	✓	✓			✓	CT ; Vib ; N	NDS+ CD	NSGAII; NSGAIII		
Li et al. [2019]	FJSP	<i>E</i>	✓	✓				T_{max} ; C_{max} ; ML	NDS+ RPD	ICA		
Zhang et al. [2019a]	JSP	<i>E</i>	✓	✓						GEP	EVP	
Liao and Wang [2019]	JSP	<i>EC</i>	✓			✓		PC ; CuS	Sum	GA		TrT
Far et al. [2019]	FJSP	<i>EC</i>	✓			✓		PC ; T	Fuzzy Sum	NSGAII	EVP	TrS; WoS
Zhang et al. [2019b]	FJSP	<i>E</i>	✓	✓				C_{max}	NDS+ CD	NSGAII		
Meng et al. [2019a]	FJSP	<i>E</i>	✓	✓	✓		✓			MILP	I/O	
Masmoudi et al. [2019]	JSP	<i>EC</i>	✓				✓			MILP	EVP	
Wang [2019]	FJSP	<i>E</i>	✓	✓	✓			C_{max} ; PC ; Q		Simul		DS
Hassani et al. [2019]	JSP	<i>EC</i>	✓					PC	Sum	MILP		

Table 2.5: Classification of the papers cited.

Ref	floor	Obj _{EE}	P	Id	S	T	In	Obj _{other}	MO App	Sol App	EE strategy	Features
2018												
Wu and Sun [2018]	FJSP	<i>E</i>	✓	✓	✓			$C_{max}; \#I/O$	NDS+ CD	NSGAII	MS; I/O	
Piroozfard et al. [2018]	FJSP	<i>TC</i>	✓	✓				T	Norm wSum	GA		
Wang et al. [2018a]	FJSP	<i>E</i>	✓	✓				PC	wSum	GA; GA+PSO		
Gong et al. [2018]	FJSP	<i>E</i>	✓					$C_{max}; LC$	wSum rank	GA		WoS
Jiang et al. [2018b]	JSP	<i>EC</i>	✓	✓			✓			WOA	MS	
Jiang and Deng [2018]	FJSP	<i>EC</i>	✓	✓						CSO		
Jiang et al. [2018a]	JSP	<i>EC</i>	✓					T	Sum	GWO		
Feng et al. [2018]	JSP	<i>E</i>	✓				✓			GA		DS
Liao and Wang [2018]	JSP	<i>TC</i>	✓	✓	✓			$PC; CT$	Norm wSum	GA		
Hemmati Far et al. [2018]	FJSP	<i>EC</i>	✓			✓		$PC; Q$	wSum	GA+ACO	EVP	TrS
Wang et al. [2018b]	FJSP	<i>E</i>	✓	✓				$C_{max}; ML$		Multi-agent Sys		DS
2017												
Mokhtari and Hasani [2017]	FJSP	<i>EC</i>	✓					$CT; Rel$	Norm wSum	GA+SA		MaS
Lei et al. [2017]	FJSP	<i>E</i>	✓	✓				ML	NDS	SFLA	MS	
Yin et al. [2017b]	FJSP	<i>E</i>	✓					$C_{max}; N$	Norm wSum	GA	MS	
Zhang et al. [2017b]	FJSP	<i>E</i>	✓	✓			✓			GEP	I/O	
Liu et al. [2017]	FJSP	<i>TC</i>		✓	✓	✓		C_{max}	NDS	FFO		TrT
Salido et al. [2017]	JSP	<i>E</i>	✓					C_{max}	Norm wSum	GA+LS	MS	DS
Yin et al. [2017a]	JSP	<i>E</i>	✓					$C_{max}; N$	Norm wSum	GA	MS	
Plitsos et al. [2017]	FJSP	<i>E</i>	✓	✓			✓	$C_{max}; ML$	Lexic	ILS		
Zhang et al. [2017a]	FJSP	<i>EC</i>	✓	✓				C_{max}	wSum	BBO	EVP; MS	
Kemmoe et al. [2017]	JSP		✓					C_{max}		GRASP		
Xu and Wang [2017]	JSP	<i>E</i>	✓	✓	✓	✓		C_{max}	wSum	GA		TrT
Zhang et al. [2017c]	FJSP	<i>E</i>	✓	✓			✓	$C_{max}; ML$		Game theory		DS; SDST
Raileanu et al. [2017]	JSP	<i>E</i>	✓	✓				C_{max}		Simul	MS	
Giglio et al. [2017]	JSP	<i>EC</i>	✓	✓				PC	-	MILP	MS	SDST; BS; Inventory
2016												
Zhang and Chiong [2016]	JSP	<i>E</i>	✓	✓				wT	NDS+ Dens	moGA+ILS	MS	
Salido et al. [2016b]	JSP	<i>E</i>	✓					C_{max}	Norm wSum	GA	MS	
Liu et al. [2016]	JSP	<i>E</i>		✓	✓			wT	NDS+ CD	NSGAII	I/O	
Zhang et al. [2016]	JSP	<i>E</i>		✓				$C_{max}; wT$		GA		DS
Xu et al. [2016]	FJSP	<i>E</i>	✓					$C_{max}; PC; Q; RM$		BA		
Yang et al. [2016]	FJSP	<i>E</i>	✓					C_{max}	NDS+ CD	NSGAII		
Samukawa and Suwa [2016]	JSP		✓					C_{max}		MIP		
Salido et al. [2016a]	JSP	<i>E</i>	✓					C_{max}	wSum	CP	MS	
Escamilla et al. [2016]	JSP	<i>E</i>	✓					C_{max}	Norm wSum	GA	MS	
2015												
May et al. [2015]	JSP	<i>E</i>		✓	✓			C_{max}	Dom + Dens	moGA; SPEAII	I/O	
He et al. [2015]	FJSP	<i>E</i>	✓	✓				C_{max}	Norm wSum	NPA		Tools
Dai et al. [2015]	FJSP	<i>E</i>	✓	✓				C_{max}		GA+SA		JPP
Lei and Guo [2015]	FJSP	<i>TC</i>	✓	✓				C_{max}	Lexic	VNS		WoS
Zhang et al. [2015]	FJSP	<i>TC</i>	✓			✓		$C_{max}; ML; WIP$	NDS+ CD	NSGAII		TrT
Tang and Dai [2015]	JSP		✓	✓	✓			C_{max}		GA+SA	MS	
Garcia-Santiago et al. [2015]	FJSP	<i>E</i>		✓	✓					HSA	I/O	BS; SDST
2014												
Liu et al. [2014]	JSP	<i>E</i>		✓				wT	NDS+ CD	NSGAII		
Jiang et al. [2014]	FJSP	<i>E</i>	✓					$C_{max}; PC; Q$	NDS+ CD	NSGAII		
Ichoua and Pechmann [2014]	JSP	<i>PP</i>	✓					$C_{max}; wTE$	wSum	TS		
Pach et al. [2014]	FJSP	<i>E</i>		✓	✓			C_{max}		Simul	I/O	DS

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Chapter 3

Energy-efficient Job Shop Scheduling Problem with Transport Resources considering Speed Adjustable Resources

Energy-efficient Job Shop Scheduling Problem with Transport Resources considering Speed Adjustable Resources

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This work extends the energy-efficient job shop scheduling problem with transport resources by considering speed adjustable resources of two types, namely: the machines where the jobs are processed on and the vehicles that transport the jobs around the shop-floor. Therefore, the problem being considered involves determining, simultaneously, the processing speed of each production operation, the sequence of the production operations for each machine, the allocation of the transport tasks to vehicles, the traveling speed of each task for the empty and for the loaded legs, and the sequence of the transport tasks for each vehicle. Among the possible solutions, we are interested in those providing trade-offs

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between makespan and total energy consumption (Pareto solutions). To that end, we develop and solve a bi-objective mixed-integer linear programming model. In addition, due to problem complexity we also propose a multi-objective biased random key genetic algorithm that simultaneously evolves several populations. The computational experiments performed have shown it to be effective and efficient, even in the presence of larger problem instances. Finally, we provide extensive time and energy trade-off analysis (Pareto front) to infer the advantages of considering speed adjustable machines and speed adjustable vehicles and provide general insights for the managers dealing with such a complex problem.

Keywords: Job shop scheduling problem · Transport resources · Energy efficiency · Mixed integer linear programming model · BRKGA · Multi-population

1 Introduction

The Job shop scheduling problem (JSP) consists of a set of jobs and a set of machines. Each job comprises several operations that must be processed in a given order and is processed, without preemption, on one machine at a time. Each operation is to be processed on a pre-specified machine during a pre-determined time. Each machine processes one operation at a time without interruptions. A solution to the JSP consists of a sequence of operations for each machine such that a given performance measure is optimized. Over the years several performance measures have been considered; the most common being the minimization of the makespan.

In the JSP, the transport of the jobs is ignored. However, since each job needs to be processed on multiple machines, whenever an operation is completed the corresponding job needs to be transported to the machine processing its next operation. The JSP either assumes that the traveling time between machines is negligible or that it is added to the processing time; this way also ignoring the transport equipment. The need to incorporate transport resources and traveling times, at least in some production systems, has already been recognized by the academic community that has already been addressing the job shop scheduling problem with transport resources (JSPT). The JSPT extends the JSP by considering transport tasks and transport resources (vehicles). Therefore, it also requires the allocation of each transport task to a vehicle as well as the sequencing of the transport tasks for each vehicle.

The JSPT considers a set of jobs, each comprising a set of ordered operations, a set of machines, where the operations are processed on, and a set of vehicles that transport the jobs around the shop-floor. The jobs are initially available at the load/unload area (LU) from where they are transported to the machines processing their first operation¹. After an operation is completed, the corresponding job is transported to the machine processing its next operation until all its operations are completed. Vehicles can transport one job at a time and machines can process one operation at a time. Both transport and processing have to be performed without preemption. A job may have to wait either for a machine, if it arrives at the machine before the machine has completed its previous operation, or for a vehicle if the vehicle arrives at the machine to pick up the job after the job operation is completed. Hence, job processing and job transportation are intertwined and need to be scheduled simultaneously. Relevant industrial applications of the JSPT can be found in many different fields, such as automotive, electronics, food and beverage, paper, healthcare, and distribution and retail, among others [see, e.g., [Fontes et al., 2023](#), and the references therein.] For recent works on the JSPT see, e.g., [[Fontes et al., 2023](#), [Fontes and Homayouni, 2019](#), [Ham, 2020](#)].

¹Some authors consider that the jobs are initially located at the machines where their first operation is processed on.

Due to stricter environmental regulations, volatile energy prices, and the increasingly growing energy demand, manufacturing companies need to reduce their energy consumption. Therefore, energy efficiency has recently become the research focus in manufacturing systems, particularly regarding scheduling problems. Although energy efficiency in manufacturing systems can be addressed in many ways, such as adopting renewable resources, using improved machinery, and redesigning products and production processes, researchers have proved energy-efficient scheduling to be an effective way of reducing energy consumption. Additionally, scheduling optimization is easier to apply to existing systems and requires far less capital investment, if at all, making it more widely applicable; especially for small and medium enterprises (SMEs) [Fernandes et al., 2022, Para et al., 2022, Lohmer and Lasch, 2021, Bansch et al., 2021, Gao et al., 2020, Dolgui et al., 2019, Gahm et al., 2016]. SMEs, typically, represent 99% of all businesses, provide about 60% of the employment, and account for approximately 13% of the global energy consumption. Therefore, helping SMEs to use energy more efficiently will benefit the SMEs, by reducing their cost base, while simultaneously boosting national productivity [EIA, 2017].

Energy-efficient scheduling aims at lowering energy consumption while providing the same level of service. Hence, works on energy-efficient scheduling look for trade-off solutions by solving a multi-objective scheduling problem. Typically, researchers balance an efficiency production measure such as makespan, tardiness, and machine workload, with an efficiency energy measure, usually, energy consumption. Most research on energy-efficient scheduling approaches the problem by either minimizing or restricting energy consumption, that is, by considering a different or an additional objective function [Zhao et al., 2022, Wang et al., 2022, Ren et al., 2021, Jiang et al., 2020, Yin et al., 2017, Raileanu et al., 2017, Salido et al., 2016, May et al., 2015] or imposing energy constraints [Lei et al., 2018, Zhang et al., 2016, Xu et al., 2016, Tang and Dai, 2015]. Although most works minimize energy consumption, there are a few works that minimize energy costs or carbon emissions and two works that minimize the peak power consumption [Fernandes et al., 2022]. Regarding the imposed constraints, although the majority of the studies impose limits on energy consumption [e.g., Zhang et al., 2016, Xu and Wang, 2017, Tang and Dai, 2015], some researchers have imposed limits on power consumption [e.g., Kemmoe et al., 2017, Carlucci et al., 2021]. In these works, solving the problem requires the usual decisions (the sequence of operations for each machine in the JSP and also the allocation of each task to a vehicle and the sequence of tasks for each vehicle in the JSPT).

Besides introducing new objective functions or constraints, some authors also incorporate additional problem features that lead to additional decision-making variables, namely: multi-state machines, see, e.g., [González et al., 2022, Wei et al., 2021, Liu et al., 2016, May et al., 2015, Liu et al., 2014] and speed adjustable machines, see, e.g., Wen et al. [2022], Xin et al. [2021], Yin et al. [2017], Salido et al. [2016], Zhang and Chiong [2016].

In the former case, one must also decide on the machine state between consecutive operations, whenever the machine has to wait for a job (leave it idle, switch it off or into standby mode). Regarding the latter, the machine processing speed has also to be chosen. These new problem features lead to two strategies that can be used to improve energy efficiency, namely: i) switching machines into a power-saving mode (turning machines off or to a stand-by mode) while idle and turning them back on again when processing restarts [Gong et al., 2021, May et al., 2015] and ii) controlling machines working speed by deciding on the speed with which machines process each operation [Zhang and Chiong, 2016, Salido et al., 2016, Lei et al., 2017]. The first strategy features additional decisions regarding machine state between consecutive operations. Hence, it may lead to a reduction on the non-processing energy consumption without affecting operations' completion times. On the other hand, the second strategy impacts the total energy consumption since by changing the machines working speed we are changing the machines power requirements as well as the processing times. Additionally, by changing the machines working speed, one changes the completion time of one or more operations. These changes may lead to a decrease or an increase of the idle times between consecutive operations, which may, in turn, lead to changes in the non-processing energy consumption. Furthermore, changing the completion time of one or more operations affect the job completion time, and even the completion time of the whole set of jobs (makespan). Therefore, the use of this strategy needs to balance energy consumption/costs and production time measures, such as makespan, tardiness, and earliness [Fontes et al., 2023].

The possibility of adjusting the resources working speed is an immediate result of the current and predicted advancements on the Internet of Manufacturing Things (IoMT) in the context of Industry 4.0. For example, speed adjustable AGVs are used by Sweden's largest automobile manufacturer - Volvo Cars [Riazi and Lennartson, 2020, Riazi et al., 2020]. Their Gothenburg plant spans over an area of roughly 85 000 m² consisting of several robot cells and conveyors. AGVs are used to transport racks of raw sheet metal parts from the inbound conveyors to robot cells for various processes as well as the empty racks from the robot cells to the outbound conveyors.

At a higher working speed, the operational time decreases at the cost of higher power consumption and vice versa. By adjusting the working speed of some resources, one may reduce resource idle time as well as energy consumption without impacting productivity. Thus, improving energy efficiency.

Riazi et al. [2020] have shown that the most important factors in energy consumption of AGVs are their traveling speeds and traveling distances. Their experiments, evaluated on a real large-scale manufacturing plant (Volvo Cars), demonstrated that the reduction of the traveling speed leads to energy savings and also that such savings can be accomplished while optimizing the productivity-related performance criteria. In another work [Riazi and

[Lennartson, 2020](#)] it is shown how to use speed management for conflict-free scheduling and routing of AGVs in a real large-scale manufacturing plant (Volvo Cars).

The speed adjustment strategy has mainly been considered for manufacturing machines (in the JSP) and only recently it has been considered for transport resources (in the JSPT). The consideration of speed adjustment for both machines and vehicles is not only very recent but also very rare. As far as we know, there are only two works on the energy-efficient JSPT (EEJSPT) in which the operating speed of both machines and vehicles can be adjusted [[Homayouni and Fontes, 2021a](#), [Wen et al., 2022](#)].

The job shop scheduling problem is a NP-hard problem [[Garey et al., 1976](#)]; thus, its extensions, i.e., JSPT and EEJSPT, are also NP-hard as, in addition, they include deciding on the vehicles assignment and sequencing and determining the speed of the machines and of the vehicles.

The first work addressing the EEJSPT, in which the operating speed of both machines and vehicles can be adjusted, is that of [[Homayouni and Fontes, 2021a](#)] and it proposes a bi-objective mathematical programming model. In here, we extend that work by presenting and solving a modified version of their model, which allows for choosing different speeds for the empty and the loaded travel legs of each transport task. [Wen et al. \[2022\]](#) also propose mathematical programming models to address the EEJSPT. Our work extends their work in several ways, namely: i) their models are single objective (both minimize the energy consumption and while one disregards the makespan, the other imposes a limit on its value) while ours is bi-objective; ii) their problem definition includes a single vehicle, which is not very realistic; and iii) only decelerating decisions are allowed. Additionally, we also propose a multi-objective multi-population biased random key genetic algorithm.

As the EEJSPT is NP-hard, the mathematical programming models can only be solved for small-sized problem instances. Thus, we also develop a multi-objective multi-population biased random key genetic algorithm (multi-objective mpBRKGA) that finds effective solutions efficiently. This is the first heuristic approach proposed for the EEJSPT with adjustable operating speeds both for machines and vehicles. To assess the efficacy and efficiency of the proposed multi-objective mpBRKGA we compare its output with that of the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a well established multi-objective metaheuristic that is frequently used to benchmark the performance of other metaheuristics. Lastly, we provide extensive time and energy trade-off analysis (Pareto front) to infer on the advantages of considering speed adjustable machines and speed adjustable vehicles in order to provide general recommendations for the managers dealing with such problems.

The main contributions of this work are several: First, we investigate a relevant and challenging problem, the integrated production and transport scheduling in a job shop setting considering speed adjustable resources (machines and vehicles), that has not yet been the subject of much research. Second, we develop a novel bi-objective MILP model to

formulate the investigated problem and propose a solution approach, which combines the “lexicographic” and ϵ -constraint methods, to approximate the true Pareto front (PF^*) for small sized-problem instances (with up to 10 jobs, six machines, six vehicles, and 40 operations). Third, we propose a multi-objective multi-population biased random key genetic algorithm (multi-objective mpBRKGA) capable of finding Pareto fronts (PF) that closely lie on the PF^* and are well spread and uniformly distributed over the PF^* . Fourth, by adapting literature instances for the job shop scheduling problem with speed adjustable machines, we propose and make available to the research community two sets of instances for this problem. Finally, we provide extensive computational experiments to assess the efficacy of the developed models and provide relevant managerial insights since by adjusting the speed of the resources we are able to obtain solutions that improve both on the production time (makespan) and on the energy consumption.

The remaining sections of this paper are organized as follows. Section 2 provides a brief review of the most recent and the most relevant literature on the energy-efficient JSP and JSPT. A description of the problem being addressed and its mathematical formulation are presented in Section 3. The multi-objective mpBRKGA is proposed in Section 4. Section 5 reports and discusses the computational experiments carried out and the results obtained. Finally, Section 6 draws some conclusions and points out future research directions.

2 Literature Review

Energy-efficient scheduling problems have been attracting the attention of both researchers and practitioners, particularly in the last decade. Although several energy-efficient works considering job shop environments have been reported, the energy-efficient job shop scheduling problem with transport resources (EEJSPT) has yet to be addressed. Hence, this section reviews works on the two closest related problems: the energy-efficient job shop scheduling problem (EEJSP) and the job shop scheduling problem with transport resources (JSPT).

2.1 Energy-efficient JSP

Several works on the EEJSP have been reported, for a recent review see the comprehensive review in [Fernandes et al., 2022].

Most of the studies approach the EEJSP by solving the JSP while optimizing an energy-related objective function. Nevertheless, a few papers address energy efficiency concerns by imposing an upper limit on the total energy consumption (see, e.g., [Zhang et al., 2016, Xu et al., 2016, Tang and Dai, 2015, Lei et al., 2018, Xu and Wang, 2017]) or on the peak power consumption (e.g., [Kemmo et al., 2017, Samukawa and Suwa, 2016, Carlucci et al., 2021, Masmoudi et al., 2019]). However, works in these lines of research propose no active strategy to change energy consumption and hence improve energy efficiency.

Several authors have proposed active energy changing strategies by resorting to machine characteristics, namely: machines with multiple energy states and speed adjustable machines, i.e., machines that can process the operations at various speed levels. In the former case, the multiple machine energy states include: active – when the machine is processing an operation (normal energy consumption); idle – when a machine is on, but not processing an operation; and off – when a machine is shut down (zero energy consumption). The energy-saving strategy consists of placing machines into a lower energy consumption state while not processing operations (idle). Some of the works considering this strategy include decisions on turning off idle machines (see, e.g., [Wu and Sun, 2018, Liu et al., 2016, May et al., 2015, Meng et al., 2019, Pach et al., 2014, Zhang et al., 2017, Rakovitis et al., 2022, Caldeira et al., 2020]), while others include decisions on switching them to a stand-by mode (see, e.g., [Li et al., 2020b, Wei et al., 2021, Xu et al., 2022, Li et al., 2020a]). A few works are more realistic, as they also include machine transition states such as warming up and ramping down [González et al., 2022, Gong et al., 2019, Garcia-Santiago et al., 2015]. More recently, the latter (speed adjustable machines) has been gaining ground as the former may lead to a spike in power consumption and require a setup time when the machines are turned back on and also because frequent turn on and turn off may damage the machines. Additionally, as the machines processing speed, processing time, and power requirements are all constant, minimizing the total energy consumption amounts to minimizing the total machines' idle time; since only the non-processing energy consumption can be reduced [e.g., Afsar et al., 2022]. Therefore, recent works on the EEJSP favor the strategy that involves controlling the machines processing speed by resorting to speed adjustable machines [see, e.g., Wu and Sun, 2018, Zhang and Chiong, 2016, Lei et al., 2017, Salido et al., 2016, He et al., 2021, Amelian et al., 2022, Wei et al., 2022].

EEJSP works considering speed adjustable machines also require determining the speed level at which each operation is processed. Processing operations at a higher speed level leads to a shorter processing time. However, it, usually, also implies a higher power demand and thus a higher energy consumption. Clearly, there exists a conflict between traditional scheduling objectives (which normally deteriorate as the processing time increases) and the total energy consumption (which decreases as the processing time increases); therefore, a trade-off must be made between the two types of objectives. However, as pointed out by Fernandes et al. [2022], adjusting the working speed of some resources may result in a lower energy consumption without impacting productivity. For example, machines finishing their activities ahead of time can have their processing speed reduced for, at least, some of the operations without affecting the job completion time or makespan. By doing so the energy consumption associated with those operations is reduced. Moreover, such reduction may also lead to a reduction in non-productive energy consumption, since the idle time of those and/or other machines may also be reduced.

The EEJSP with speed adjustable machines was first introduced by [Tang and Dai \[2015\]](#). They proposed the first MIP model along with a combined Genetic and Simulated Annealing Algorithm (GSAA) to improve on a given schedule by deciding on the processing speed of each operation. Thus, given a schedule, sequence of operations, and the corresponding makespan when all operations are processed at a given (nominal) speed, they minimize energy consumption by adjusting the operations processing speed without exceeding the makespan. The efficacy of the GSAA was tested on 27 small-sized instances (with five, seven, or 10 operations and three, five, or seven machines) and five larger ones (with 10, 15, or 20 operations and 10, 15, or 20 machines). The computational results have shown that at (almost) no makespan cost, the GSAA can lead to energy savings ranging from 5% to 10% for the smaller instances. However, for the larger ones, this is no longer possible. Nevertheless, energy savings between 0.5% and 4% can be achieved but at the cost of a larger makespan; between 1% and 7% larger.

Recently, [Zhang and Chiong \[2016\]](#) addressed an EEJSP problem version that considers a set of jobs, each with m operations that must be processed on m machines (all jobs are processed once on each machine), for which they propose a multi-objective GA that optimizes the total weighted tardiness and the energy consumption. The GA incorporates two local search strategies (one for the tardiness and another for the energy) that attempt to improve on the tardiness by swapping disjoint pairs of adjacent operations on each machine and on the energy consumption by decreasing the processing speed of non-delaying operations. The encoding used consists of two parts: one for operations sequencing and another for speed assignment; each part being a matrix with as many rows as machines and as many columns as operations. For each operation and each machine, the matrices provide, respectively, the operations priority order and processing speed. The computational experiments reported show that the proposed algorithm outperforms the well-known NSGA-II [\[Deb et al., 2002\]](#).

Another GA is proposed in [Salido et al. \[2016\]](#). The encoding scheme also has two parts: a $2n$ vector is used for a problem with n operations. Odd-indexed elements represent the operations and even-indexed elements the corresponding processing speeds. Although two objective functions are considered, the energy consumption and the makespan, the GA uses a single objective function that is the weighted sum of the normalized objective values. The GA performance was compared with that of the commercial solver IBM ILOG CPLEX CP Optimizer on a set of problem instances they also proposed. The instances were generated by extending existing benchmark instances with three different processing times and corresponding energy consumption for each operation, representing three speed levels. The results reported show that the GA is as good or better than the CP optimizer for small instances and outperforms it for large ones.

More recently, [Lu et al. \[2021\]](#) proposed a multi-objective memetic algorithm that borrows the local search ideas of [Zhang and Chiong \[2016\]](#) and uses a greedy heuristic to determine the operations processing speed. After a schedule is obtained, operations processing is decelerated as much as possible without affecting any other operations. Through computational experiments, they compared the performance of the algorithm with and without the local search mechanism and have shown that both the local search strategy and the deceleration heuristic are effective. However, no comparisons with any other works or methods are provided.

Among the works addressing EEJSPs, a few consider the transport energy consumption. Some of these works are discussed next, within the JSP with transport resources subsection.

2.2 JSP with transport resources

The job shop scheduling problem with transport resources (JSPT) has been extensively studied in the past three decades with time related objective functions; the most common being the minimization of the makespan. The first formulation of the JSPT is due to [Bilge and Ulusoy \[1995\]](#) that developed a mixed integer linear programming model. However, solutions are obtained by a sliding time window heuristic. Since then, several authors have addressed the JSPT; mainly proposing (meta)heuristic approaches due to its NP-hard nature [[Fontes and Homayouni, 2019](#)]. For example, [Abdelmaguid et al. \[2004\]](#) proposed a two stage GA; [Reddy and Rao \[2006\]](#) a hybrid GA; [Deroussi et al. \[2008\]](#) a simulated annealing (SA) algorithm; [Zhang et al. \[2012\]](#) a hybrid GA and TS algorithm; [Lacomme et al. \[2013\]](#) a memetic algorithm; [Zheng et al. \[2014\]](#) a TS algorithm; and [Baruwa and Piera \[2016\]](#) an anytime layered search algorithm. Regarding exact solution approaches, recently [Fontes and Homayouni \[2019\]](#) proposed a MILP model, which is solved to optimality for almost all small-sized benchmark instances. More recently, [Ham \[2020\]](#) proposed a constraint programming model and also solved most of the small-sized benchmark instances.

In contrast to the recent research trend being followed for the JSP, transport issues have rarely been considered within the energy-efficient context. Furthermore, whenever considered, only the required energy to transport the jobs is taken into account. This energy is simply calculated by multiplying the traveling time by the vehicle's power consumption. Vehicles are not assigned to the transport of jobs and are not scheduled as it is assumed that there is an unlimited number of vehicles. This is, obviously, an unrealistic assumption in most applications. Having a limited number of vehicles not only requires the assignment of the transport tasks to vehicles and the sequencing of the tasks to be performed by each vehicle but may also require additional vehicle empty traveling (to pick up a job) and imply waiting times by both machines (while jobs are being transported) and vehicles (while operations are being processed). Moreover, ignoring vehicles during the scheduling stage implies that the assignment of transport tasks and their sequencing is to be decided on the

shop-floor. This in turn implies that processing and transporting decisions are made separately and sequentially. Additionally, machines processing times and vehicles traveling times are constant as no speed adjustment is considered.

Recently, [Xu and Wang \[2017\]](#) proposed a rolling horizon scheduling approach, based on a feedback control method, to determine the sequence of operations on each machine while minimizing the makespan and the total energy required to process production operations, to warm up machines, to keep machines running while idle, and to transport jobs. The approach considers a single objective function obtained by the weighted sum of the two objectives, which is updated by iteratively adjusting the weights based on the feedback of the actual energy consumption and makespan in previous periods. But they considered that an unlimited number of vehicles is available to transport the jobs. A similar problem definition is considered by [Dai et al. \[2019\]](#) that proposed a hybrid algorithm combining an estimation of distribution algorithm, which is responsible for evolving a population of solutions, with a simulated annealing algorithm, which in some generations searches for neighbor solutions. They also proposed a MILP model that optimizes the weighted sum of the normalized makespan and the normalized total energy consumption, which is not solved.

More recently, [Ren et al. \[2020\]](#) also addressed a JSP with unlimited vehicles in which all jobs have to be processed once in every machine. First, they solved a JSP by resorting to a non-dominated sorting genetic algorithm II (NSGA-II) that optimizes the makespan, the tardiness, and the energy consumption. The energy consumption is given by the energy required by machines (start-up and shut-down, idle, and processing) and the energy required by vehicles to transport the jobs. Then, in a second stage, they used an ant colony optimization algorithm to group the transport tasks and construct routing paths for the vehicles while minimizing the number of vehicles used and the energy consumption.

Most recently, [Zhou and Lei \[2021\]](#) addressed the JSPT, since they considered a limited number of vehicles. Hence, vehicles have to be assigned to the transport tasks and the sequence of tasks of each vehicle has to be determined. Nevertheless, only a single processing speed level and a single traveling speed level are considered. The problem is formulated as a bi-objective mathematical model that minimizes the makespan and the total energy consumption by both machines (processing and idle) and vehicles (loaded and empty travel). Solutions were found by a grey wolf optimization (GWO) algorithm. Furthermore, the GWO incorporates a heuristic that finds and resolves vehicle conflicts by imposing that one vehicle waits or moves backward until the other completes its assignment. They also proposed 32 problem instances with 10 and up to 500 jobs (each with a single operation) that are used in the computational experiments considering three settings, namely: six machines and one AGV, six machines and two AGVs, and eight machines and two AGVs. They compared the performance of their algorithm with literature approaches, including the NSGA-II

and concluded that their approach provides solutions with a relatively higher quality.

As discussed earlier, the JSPT in which the operating speed of both machines and vehicles can be adjusted was first introduced by [Homayouni and Fontes \[2021a\]](#). They propose a bi-objective MILP model to determine simultaneously the sequence of operations on each machine, the machine processing speed for each operation, the vehicle assignment for each transport task, and the vehicle travelling speed for each leg of each transport task. The objective functions considered are the makespan and the total energy consumption - energy required both by the machines to process the production operations and by the AGVs to perform the transport tasks. The MILP model is solved to optimality, for small-sized problem instances, by employing a strategy that combines the “lexicographic” and the ϵ -constraint methods. The numerical analysis demonstrates that by carefully choosing the resources operating speed it is possible to decrease substantially the energy consumption without increasing the makespan.

A similar yet limited version of the problem is considered in [\[Wen et al., 2022\]](#). The problem addressed i) includes only a single vehicle (a gripper robot) to transport the jobs, which is less realistic and eliminates vehicle assignment decisions; 2) does not consider machine buffers, which is also less realistic and removes flexibility; and 3) allows only to decrease the operating speeds. The authors propose two single objective MILP models: both minimize the total energy consumption and while one disregards the makespan, the other imposes a limit on its value. Since no trade-off solutions are easily found, it is harder to provide managerial insights and recommendations. They solved a set of ten small-sized problem instances that showed that the energy consumption can be decreased (15% on average) at the cost of increasing the makespan (20% on average).

In summary, several works have been published on the energy-efficient JSP with speed adjustable machines. In contrast, the energy-efficient JSPT with speed adjustable machines and vehicles has just very recently been considered for the first time [\[Homayouni and Fontes, 2021a\]](#). All previous works taking into account the transport energy consumption do not consider transport resources. They address the JSP and calculate vehicle energy consumption by multiplying travel time by vehicle power consumption, which amounts to adding a constant energy consumption value to the machines energy consumption since there is an unlimited number of vehicles and traveling times and power requirements are constant and known. As discussed above, there are only two works that consider the JSPT with speed adjustable machines and vehicles [\[Homayouni and Fontes, 2021a, Wen et al., 2022\]](#) and the work proposed here extends both these works. The former is extended by allowing to decide on the vehicle speed for each leg of each transport task, while the latter is extended by considering several vehicles, machine buffers, and the possibility of decreasing or increasing operating speed, by proposing a better solution approach (bi-objective optimization) as it allows to obtain a set of trade-off solutions (Pareto Front). Finally, we also

propose the first heuristic approach (a multi-objective and multi-population biased random key genetic algorithm) since both previous works only propose an exact solution approach, which given the NP-hard nature of the problem only allow to solve small-sized problems.

Hence, this work extends current literature since it addresses the energy-efficient JSPT, which clearly needs to be further researched. Furthermore, this research may also significantly impact companies as their energy consumption and energy costs can be reduced while simultaneously boosting their productivity (see Section 5.5).

3 Problem Definition and formulation

The EEJSPT under study concurrently tackles five interdependent combinatorial optimization problems: i) production operations scheduling for each machine, ii) processing speed assignment for each production operation, iii) vehicle allocation to each transport task (associated with each production operation), iv) transport tasks scheduling for each vehicle, and v) travel speed assignment for both the empty and the loaded journey legs of each transport task.

The EEJSPT considers a set $\mathcal{J}$ of jobs, each of which composed of a set $\mathcal{O}_j = \{o_{j1}, o_{j2}, \dots, o_{jn_j}\}$ of n_j ordered production operations, a set $\mathcal{M}$ of machines to process the production operations, and a set $\mathcal{V}$ of vehicles to move the jobs around the shop-floor.

Let $N = \sum_{j \in \mathcal{J}} n_j$ be the total number of operations, $\mathcal{O} = \bigcup_{j \in \mathcal{J}} \mathcal{O}_j$ be the set of all operations, and $\mathcal{O}' = \bigcup_{j \in \mathcal{J}} o_{j1}$ be the set of first operations of all jobs.

As usual, each machine processes one operation at a time in a non-preemptive manner and each job can only be processed on one machine at a time. However, machines can be operated at different speed levels. The available speed levels depend both on the machine and on the operation. As which machine processes each operation is known, we can define a set of speed levels for each operation; let $\mathcal{P}_l, l \in \mathcal{O}$ be such set. Additionally, we also know the energy consumption of each machine to process each operation at each processing speed level ($e_l^p, p \in \mathcal{P}_l, l \in \mathcal{O}$).

Following on the work in [Zhang and Chiong, 2016, Salido et al., 2016], we consider that a machine cannot be turned off until all operations assigned to it have been completed. This assumption reflects applications in the textile and metal manufacturing industries, among others, where turning a machine off and on leads to a spike in the power consumption and requires a considerably large setup time and/or cost. However, when not processing the machines can wait for the next job in a “stand-by” mode, in which the energy consumption is negligible. Additionally, we assume non sequence dependent set-up time² between consecutive operations.

²In the presence of a non-sequence dependent set-up time, we simply add the set-up time to the operation processing time.

All jobs are initially available in the load/unload area (LU), from where each job is transported by a vehicle to the machine processing its first operation. Once the first operation is completed, the job is transported by a vehicle to the machine processing the second operation, and so on until the job reaches the machine processing its last operation. As usual, machines have input and output buffers where jobs may have to wait for the machine or for a vehicle. Hence, whenever a machine/vehicle completes an operation/task it can start the next operation/task. Obviously, machines may have to wait for the delivery of a job and vehicles may have to wait for the completion of an operation.

All vehicles are initially available at the LU and remain wherever they finish a transport task (dwell point) until the start of the next one. Therefore, an empty travel, to pick up a job, may be required since the current dwell point of a vehicle may be different from the origin of its next task (either the LU or the machine where the previous operation of the job has been completed). The vehicles are identical and any vehicle can transport any job. Vehicles can travel at any of the average speed levels in set $\mathcal{V}$ with a predefined and speed level dependent power consumption. The power consumption also depends on whether the vehicle is empty or loaded (carrying a job). Since the floor layout is known and the transport tasks are non-preemptive, the travel time and the energy consumption between any two locations (at a specific average speed level) are known both for empty and loaded journey legs. As was the case for machines, it is assumed that the vehicles are switched to the “stand-by” mode while idle, with a negligible energy consumption.

Following on the work of [Fontes and Homayouni \[2022\]](#), we define a set $\mathcal{F}$ of pairs of operations that cannot be processed/transported consecutively. This way, we can reduce the size of the MILP model as several variables and constraints are excluded. This set contains pairs of operations including the same operation twice $(k, k) : k \in \mathcal{O}$ and pairs of operations of the same job that do not satisfy the precedence constraints $(k, l) : l \leq k, k, l \in \mathcal{O}_j, j \in \mathcal{J}$.

$$\mathcal{F} = \{(k, k) : k \in \mathcal{O}\} \cup \{(k, l) : l \leq k, k, l \in \mathcal{O}_j, j \in \mathcal{J}\}.$$

The MILP model we propose is a modified and improved version of that of [\[Homayouni and Fontes, 2021a\]](#), since it includes decision variables to select the travel speed level both for the empty and loaded journey legs of the transport tasks. Among all possible solutions for this problem, we are interested in those that minimize the makespan (i.e., the completion time of the last production operation) and minimize the total energy consumed to process the production operations and transport the jobs around the shop-floor.

Let us first define the parameters and decision and auxiliary variables and then provide the MILP model and its description.

Parameters:

π_l^p : Processing time of operation $l \in \mathcal{O}$ at speed level $p \in \mathcal{P}_l$;

- e_l^p : Energy consumed to process operation $l \in \mathcal{O}$ at speed level $p \in \mathcal{P}_l$;
- τ_{kl}^v : Empty travel time from machine $m_k, k \in \mathcal{O}$ to the LU or to machine $m_{l-1}, l \in \mathcal{O}$, depending, respectively, on whether $l \in \mathcal{O}'$ or not, at speed level $v \in \mathcal{V}$;
- τ_{0l}^v : Empty travel time from the LU to the LU (no traveling being required) or to machine $m_{l-1}, l \in \mathcal{O}$, depending, respectively, on whether $l \in \mathcal{O}'$ or not, at speed level $v \in \mathcal{V}$;
- θ_l^v : Loaded travel time from the LU or machine m_{l-1} , depending, respectively, on whether $l \in \mathcal{O}'$ or not, to machine $m_l, l \in \mathcal{O}$ at speed level $v \in \mathcal{V}$;
- ε^v : Empty vehicle power consumption at speed level $v \in \mathcal{V}$;
- ε^v : Loaded vehicle power consumption at speed level $v \in \mathcal{V}$;

Decision and Auxiliary Variables:

- w_{kl}^p : Binary variable set to 1 if a machine processes consecutively operations $k \in \mathcal{O}$ and $l \in \mathcal{O}$ and the latter is processed at speed level $p \in \mathcal{P}_l$ and set to 0 otherwise (recall that w_{kl}^p is only defined if $(k, l) \notin \mathcal{F}$);
- $f_{lm_l}^p$: Binary variable set to 1 if operation $l \in \mathcal{O}$ is the first operation on machine m_l and is processed at speed level $p \in \mathcal{P}_l$ and set to 0 otherwise;
- t_{lm_l} : Binary “dummy” variable set to 1 if operation $l \in \mathcal{O}$ is the last operation on machine m_l and set to 0 otherwise;
- x_{kl}^v : Binary variable set to 1 if a vehicle transports consecutively the jobs associated with operations $k \in \mathcal{O}$ and $l \in \mathcal{O}$ and the empty travel associated with the latter is done at speed level $v \in \mathcal{V}$ and set to 0 otherwise (recall that x_{kl}^v is only defined if $(k, l) \notin \mathcal{F}$);
- χ_l^v : Binary variable set to 1 if the loaded travel associated with operation $l \in \mathcal{O}$ is done at speed level $v \in \mathcal{V}$ and set to 0 otherwise;
- y_l^v : Binary variable set to 1 if the first task of a vehicle is the empty travel associated with operation $l \in \mathcal{O}$ at speed level $v \in \mathcal{V}$ and set to 0 otherwise;
- z_l : Binary “dummy” variable set to 1 if the last task of a vehicle is the loaded travel associated with operation $l \in \mathcal{O}$ and set to 0 otherwise;
- c_l : Completion time of operation $l \in \mathcal{O}$;
- r_l : Vehicle arrival time at machine $m_l, l \in \mathcal{O}$;
- $C_{\max}$: Makespan of the production operations;

$\mathcal{E}$: Total energy consumption (production operations and transport tasks).

$$\text{Minimize: } \{C_{\max}, \mathcal{E}\} \quad (3.1)$$

Subject to:

$$C_{\max} \geq c_l, \quad \forall l \in \mathcal{O}, \quad (3.2)$$

$$\mathcal{E} = \sum_{l \in \mathcal{O}} \left(\sum_{k \in \mathcal{O}} \sum_{p \in \mathcal{P}_l} e_l^p w_{kl}^p + \sum_{p \in \mathcal{P}_l} e_l^p f_{lm_l}^p + \sum_{w \in \mathcal{V}} \chi_l^w \varepsilon^w \theta_l^w + \sum_{v \in \mathcal{V}} y_l^v \varepsilon^v \tau_{0l}^v + \sum_{k \in \mathcal{O}} \sum_{v \in \mathcal{V}} x_{kl}^v \varepsilon^v \tau_{kl}^v \right), \quad (3.3)$$

$$\sum_{p \in \mathcal{P}_l} f_{lm_l}^p + \sum_{k \in \mathcal{O}} \sum_{p \in \mathcal{P}_l} w_{kl}^p = 1, \quad \forall l \in \mathcal{O}, \quad (3.4)$$

$$\sum_{k \in \mathcal{O}} \sum_{p \in \mathcal{P}_l} w_{lk}^p + t_{lm_l} = 1, \quad \forall l \in \mathcal{O}, \quad (3.5)$$

$$\sum_{l \in \mathcal{O}} \sum_{p \in \mathcal{P}_l} f_{lm_l}^p = 1, \quad \forall m \in \mathcal{J}, \quad (3.6)$$

$$\sum_{l \in \mathcal{O}} t_{lm_l} = 1, \quad \forall m \in \mathcal{J}, \quad (3.7)$$

$$\sum_{l \in \mathcal{O}} z_l = \sum_{l \in \mathcal{O}} \sum_{v \in \mathcal{V}} y_l^v, \quad (3.8)$$

$$\sum_{l \in \mathcal{O}} z_l \leq |\mathcal{A}|, \quad (3.9)$$

$$\sum_{v \in \mathcal{V}} y_l^v + \sum_{k \in \mathcal{O}} \sum_{v \in \mathcal{V}} x_{kl}^v = 1, \quad \forall l \in \mathcal{O}, \quad (3.10)$$

$$\sum_{k \in \mathcal{O}} \sum_{v \in \mathcal{V}} x_{lk}^v + z_l = 1, \quad \forall l \in \mathcal{O}, \quad (3.11)$$

$$\sum_{v \in \mathcal{V}} \chi_l^v = 1, \quad \forall l \in \mathcal{O}, \quad (3.12)$$

$$c_l - r_l - \sum_{k \in \mathcal{O}} \sum_{p \in \mathcal{P}_l} w_{kl}^p \pi_l^p - \sum_{p \in \mathcal{P}_l} f_{lm_l}^p \pi_l^p \geq 0, \quad \forall l \in \mathcal{O}, \quad (3.13)$$

$$c_l - c_k - \sum_{p \in \mathcal{P}_l} w_{kl}^p \pi_l^p \geq M \left(\sum_{p \in \mathcal{P}_l} w_{kl}^p - 1 \right), \quad \forall k, l \in \mathcal{O}, \quad (3.14)$$

$$r_l - c_{l-1} - \sum_{v \in \mathcal{V}} \chi_l^v \theta_l^v \geq 0, \quad \forall l \in \mathcal{O} \setminus \mathcal{O}', \quad (3.15)$$

$$r_l - r_k - \sum_{v \in \mathcal{V}} x_{kl}^v \tau_{kl}^v - \sum_{w \in \mathcal{V}} \chi_l^w \theta_l^w \geq M \left(\sum_{v \in \mathcal{V}} x_{kl}^v - 1 \right), \quad \forall k, l \in \mathcal{O}, \quad (3.16)$$

$$r_l - \sum_{v \in \mathcal{V}} y_l^v \tau_{0l}^v - \sum_{w \in \mathcal{V}} \chi_l^w \theta_l^w \geq 0, \quad \forall l \in \mathcal{O}, \quad (3.17)$$

$$C_{\max}, \mathcal{E}, c_l, r_l \geq 0, \quad \forall l \in \mathcal{O}, \quad (3.18)$$

$$w_{kl}^p, f_{lm_l}^p, t_{lm_l}, x_{kl}^v, \chi_l^v, y_l^v, z_l \in \{0, 1\}, \quad \forall k, l \in \mathcal{O}, p \in \mathcal{P}_l, v \in \mathcal{V}. \quad (3.19)$$

The objective is to minimize the makespan and the total energy consumption as in expression (3.1), which are calculated by expressions (3.2) and (3.3), respectively. These constraints also imply the choice of a single processing speed level for each operation. Constraints (3.4) and (3.5) impose that each operation is preceded and followed by exactly one other operation on the same machine, unless it is the machine's first or last operation, respectively. Moreover, constraints (3.6) and (3.7) ensure, respectively, that each machine processes exactly one first operation and one last operation.

Constraints (3.8) and (3.9) ensure the same number of first and last tasks and that this number does not exceed the number of available vehicles. As was the case for operations, each travel task is preceded and followed by exactly one other travel task, performed by the same vehicle, unless it is the vehicle's first or last task, which is stated by constraints (3.10) and (3.11), respectively. These constraints also imply the choice of a single speed level for the empty travel associated with each operation. In addition, constraints (3.12) ensure that the loaded travel associated with each operation is performed at a single speed level.

An operation can only be completed once i) the corresponding job has arrived at the machine processing the operation and its processing time (at the chosen speed level) has elapsed (as in constraints (3.13)) and ii) the previous operation on the same machine has been completed and its processing time has elapsed (as in constraints (3.14), where M is a sufficiently large positive integer). Similarly, a job can only be delivered to a machine for having an operation processed after its previous operation has been completed and the job has been transported, as stated in constraints (3.15). Additionally, if the vehicle has transported some other job to have an operation processed (say $k \in \mathcal{O}$) immediately before the current one (say $l \in \mathcal{O}$), then it can only arrive at machine m_l after (i) delivering the corresponding job to machine m_k , (ii) traveling empty from machine m_k to machine m_l or to the LU if operation l is the first operation of a job, and (iii) traveling loaded to machine m_l , which is enforced by constraints (3.16). Otherwise, if it is the vehicle's first transport task, then it just needs to pick up the job and transport it to the corresponding machine, see constraints (3.17). Finally, constraints (3.18) and (3.19) define the nature of the variables.

4 The Multi-Population BRKGA

This section proposes a biased random key genetic algorithm that simultaneously evolves several populations. These populations include single objective populations as well as multi-objective populations.

Random key genetic algorithms (RKGAs) were originally proposed by Bean [1994]. In these genetic algorithms a solution is represented as a vector of random keys (RKs), i.e.,

real numbers in the interval $[0, 1]$. This vector is then decoded into a solution to the original problem and its fitness (quality) is calculated. Biased random key genetic algorithms (BRKGAs) differ from random key genetic algorithms by ensuring that one of the parents is always chosen from a subset of the solutions containing the fitter solutions (elite solutions) and by ensuring that, during recombination, the alleles of the fitter parent have a higher chance to be passed on.

A BRKGA has several good characteristics that help to manage and overcome the difficulties of complex problems such as the EEJSPT, namely: It uses a parameterized uniform crossover and avoids the use of repair operators by delegating feasibility issues to the decoder, which prevents the evolutionary process from getting stuck due to infeasibilities [Gonçalves and Resende, 2011]. The random keys chromosome representation and the introduction of new solutions (mutants) at every generation enable the exploration of the solution space. In contrast, the crossover operator and the decoder exploit the structural properties of the solutions [Eiben et al., 2003]. Finally, such characteristics remove the need to employ local search, which is frequently a very time-consuming component of the heuristics and has a negligible impact on the solutions [Drex1, 2012]. These characteristics, together with the reported good performance for a wide variety of problems, and in particular for the JSP and its variants, and the authors' previous experience clearly justify the choice of BRKGAs as the solution approach [see, e.g., Kummer et al., 2022, Kapadia et al., 2021, Xiao et al., 2020, Homayouni et al., 2020, Fontes et al., 2019, Roque et al., 2017, Fontes and Gonçalves, 2013].

The mpBRKGA proposed borrows its principles from [Fontes and Gonçalves, 2013] and evolves $\Omega + \Pi$ populations: each of the Ω populations considers one of the Ω objectives, while each of the Π populations considers simultaneously all Ω objectives. By evolving the Ω single objective populations independently and simultaneously, we are searching several areas of the solution space simultaneously. Hence, we achieve several (likely) distinct local minima. Furthermore, the Π multi-objective populations are also independently and simultaneously evolved; however, at each generation, they receive in their population the best individuals of every single objective population and every so often they also receive the best individuals of the other multi-objective populations. This way, enforcing further exploitation of the problem's solution space.

The initial populations are randomly generated. However, in 20% of the initial solutions of the single-objective populations that minimize the C_{max} the processing and the traveling speeds are set to the maximum level. Similarly, in 20% of the initial solutions of the single objective populations that minimize the $\mathcal{E}$ the processing and traveling speeds are set to the minimum level.

4.1 Evolutionary Process

The evolutionary strategy is similar for all populations. The initial population is comprised of vectors of real-valued random keys uniformly drawn from $[0, 1]$. Let P be the population size of the genetic algorithm. At each generation, individuals of the current population are sorted according to their fitness values and divided into two sets: the elite set that comprises the best N_e solutions and the non-elite set consisting of the remaining $P - N_e$ solutions. Since the BRKGA is elitist, it copies all individuals of the elite set of the current population onto the next population; this way, the BRKGA monotonically keeps the best solutions found over the search [Gonçalves and Resende, 2011]. The remaining solutions that make up the next generation are created using two different strategies. On the one hand and to keep the new population's diversity, a set of N_m new random solutions called mutants is generated, in the same manner as the initial population was. On the other hand, the characteristics of good solutions are kept by a set of $N_o = P - N_e - N_m$ offspring solutions. The offspring solutions are obtained by mating one solution from the elite set with a solution from the non-elite set and by resorting to the parameterized uniform crossover, see Section 4.3. Finally, the next population becomes the current population, and the process is repeated until some stopping criterion is met, e.g., reaching a predefined number of generations.

For each of the Ω single objective populations, the set of elite solutions comprises the best N_e solutions of the current generation, which are copied onto the next generation. Regarding the Π multi-objective populations, the N_e elite solutions are chosen from a pool of solutions containing up to $(1 + \Omega) \times N_e$ solutions. For each population, $\pi \in \Pi$ the pool of solutions is obtained by joining the best N_e solutions of the current generation of population π and those of each of the Ω single objective populations and then removing repeated solutions. Additionally, multi-objective populations exchange solutions after a pre-determined number of generations (g_{ex}). Thus, every g_{ex} generations, the pool of solutions also contains the best N_e solutions of the other multi-objective populations; having up to $(\Pi + \Omega) \times N_e$ solutions. Figure 3.1 depicts, at a high level, the evolutionary process just described.

To identify the best solutions for the multi-objective populations, we employ a non-dominated ranking procedure [Deb et al., 2002] that repeatedly uses the following three steps: i) identify all non-dominated solutions; ii) rank them with the smallest value (initially 1); and iii) remove the solutions identified in i) and increase the rank value by 1. This procedure finds several fronts (as many as rank values), each consisting of all solutions with the same rank, as shown in Figure 3.2.

To select the solutions that form the elite set, we start by choosing the solutions of the lower ranked fronts. However, it may happen that the number of solutions to choose is smaller than the number of solutions forming the front that we are choosing from. Therefore, the solutions of each front are sorted according to their contribution to diversity, here measured by the crowding distance (CD) - the normalized distance between the solution

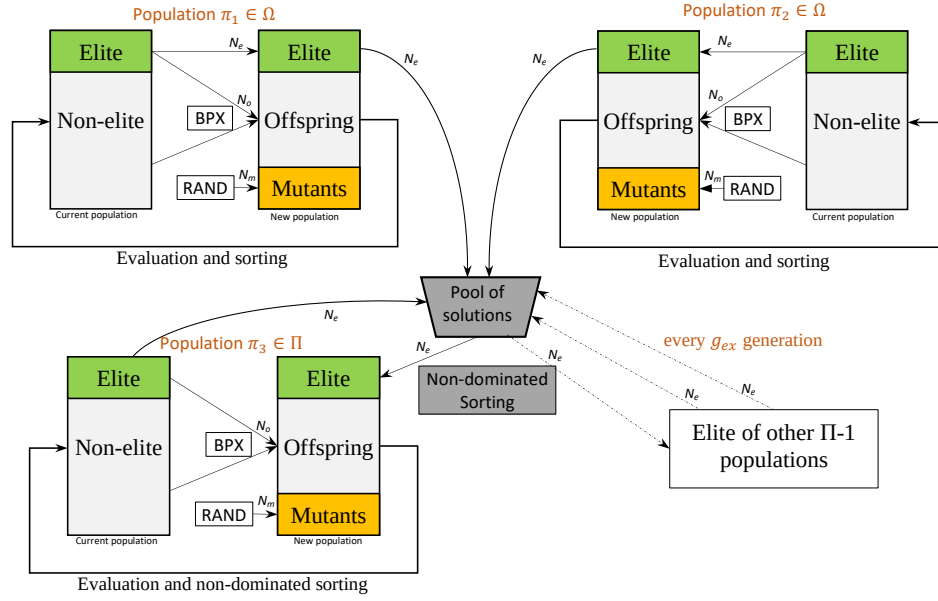


Figure 3.1: The evolutionary process of the proposed mpBRKGA: the elite solutions are copied onto the next population, some new solutions (mutant) are randomly generated to keep the diversity of the next population, and the remaining solutions of the next population are filled up with offspring. For the multi-objective populations, the elite solutions are chosen from a pool containing their own elite solutions and the ones of the single objective populations. Additionally, every so often the pool also contains the elite solutions of all other multi-objective populations.

Figure 1 Alt Text: Figure showing the evolutionary process of the proposed mpBRKGA: the elite solutions are copied onto the next population, some new solutions (mutant) are randomly generated to keep the diversity of the next population, and the remaining solutions of the next population are filled up with offspring. For the multi-objective populations, the elite solutions are chosen from a pool containing their own elite solutions and the ones of the single objective populations. Additionally, every so often the pool also contains the elite solutions of all other multi-objective populations.

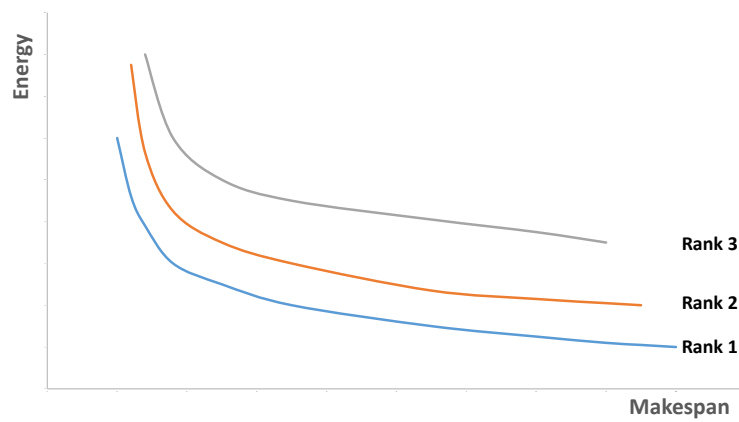


Figure 3.2: The non-dominated ranking procedure is used to identify solutions with the same rank. From the set of all solutions of a population, the non-dominated solutions are ranked 1 and then removed from the set of solutions. From the remaining solutions, the non-dominated ones are ranked 2 and then are removed from the set of solutions. This is repeated until the set of solutions is empty.

Figure 2 Alt Text: Figure showing the Fronts associated with three non-dominated ranks. The non-dominated ranking procedure is used to identify solutions with the same rank. From the set of all solutions of a population, the non-dominated solutions are ranked 1 and then removed from the set of solutions. From the remaining solutions, the non-dominated ones are ranked 2 and then are removed from the set of solutions. This is repeated until the set of solutions is empty.

and its two closest neighbor solutions.

The crowding-distance CD_l of solution l is given by the summation, over all objective functions, of the crowding distance values of each objective function CD_l^ω , see equation (3.20). To obtain crowding distance CD_l^ω of solution l for the ω^{th} objective function, we divide the difference between the objective function values ($f_{l+1}^\omega - f_{l-1}^\omega$) of its two closest neighbors (solutions $l-1$ and $l+1$) by the difference between the objective function values ($f_{max}^\omega - f_{min}^\omega$) of the boundary solutions, as given in equation (3.21) and illustrated in Figure 3.3.

$$CD_l = \sum_{\omega=1}^{\Omega} CD_l^\omega, \quad (3.20)$$

$$CD_l^\omega = \frac{f_{l+1}^\omega - f_{l-1}^\omega}{f_{max}^\omega - f_{min}^\omega}. \quad (3.21)$$

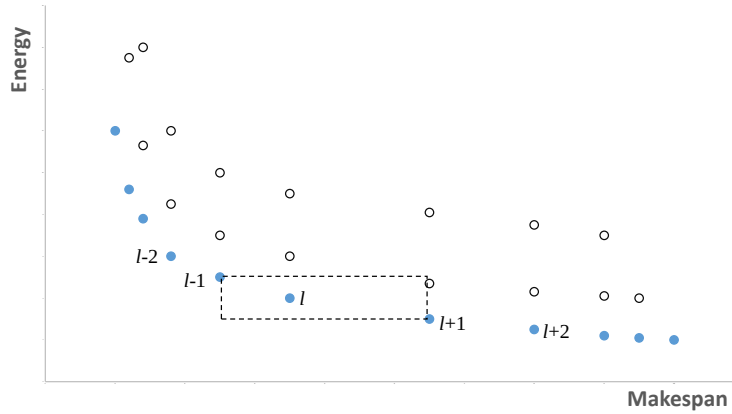


Figure 3.3: Crowding distance calculation for solution l : calculate the normalized objective distance between solutions $l-1$ and $l+1$ (the closest neighbors of solution l) for the energy consumption and the makespan and then add them up.

Figure 3 Alt Text: Figure showing how to calculate the crowding distance. For a solution l , calculate the normalized objective distance between solutions $l-1$ and $l+1$ (the closest neighbors of solution l) for the energy consumption and the makespan and then add them up.

Regardless of the population being evolved, the N_o offspring solutions are obtained by a biased parameterized uniform crossover (BPX) and the N_m mutants are randomly generated in the same manner as the initial population was. Additionally, for the single objective populations, we set the processing and traveling speeds of 20% of the mutants to the extreme values as follows: when the C_{max} is being minimized all resources are set to the highest speed level and when the $\mathcal{E}$ is being minimized all resources are set to the lowest speed

level.

The mpBRKGA, which is described in Algorithm 1, repeats the evolutionary process for a predetermined number of generations (G_{max}). Then, a pool of solutions is created by selecting the best solution of each of the Ω single objective populations and all non-dominated solutions of each of the Π multi-objective populations. Finally, the repeated solutions and the dominated solutions are removed. The remaining solutions are Pareto solutions and provide an approximation to the Pareto optimal front.

Algorithm 1 The proposed multi-population biased random key genetic algorithm

```

1: Initialization of the parameters for the mpBRKGA,
2: Generate  $\Omega + \Pi$  initial populations,
3: while stopping criteria are not satisfied do
4:   for  $\pi$  in  $\Omega + \Pi$  do
5:     Decode and evaluate the solutions,
6:     if  $\pi \in \Omega$  then
7:       Sort the solutions based on the (single) objective function value,
8:       Select the best  $N_e$  to form the elite set,
9:     else
10:      Rank the non-dominated solutions and constructs fronts,
11:    end if
12:  end for
13:  for  $\pi$  in  $\Omega + \Pi$  do
14:    if  $\pi \in \Pi$  then
15:      Create the pool of solutions,
16:      Remove repeated solutions from the pool,
17:      Select the “best”  $N_e$  solutions to form the elite set, calculating  $CD$  if needed.
18:    end if
19:    Copy the elite solutions onto the population of the next generation,
20:    Obtain  $N_o$  offspring solutions by BPX and add them to the population of the
    next generation,
21:    Generate mutants and add them to the population of the next generation,
22:  end for
23: end while
24: Create a pool with the best solutions of each of the  $\Omega$  populations and the “best” solu-
    tions of each of the  $\Pi$  populations,
25: Remove from the pool all repeated and all dominated solutions,
26: Terminate the algorithm and print the optimal PF and the extreme solutions.

```

4.2 Solution Encoding and Decoding

A solution to the EEJSPT being addressed is represented by a five-part vector with N elements each. The encoding resorts to vectors with N elements each, which could lead to a large solution space. However, the potential solution space is drastically reduced since only

feasible solutions are generated. Furthermore, such a strategy also has the advantage of dismissing the necessity of repair operators. The first part provides a sequence of operations and the second an assignment of operation processing speed levels. The other three parts refer to the transport tasks and provide a vehicle-task assignment, an empty travel speed level assignment, and a loaded travel speed level assignment. An example of such a vector is provided in Figure 3.4.a).

The decoding (mapping) of the first N genes uses the smallest position value rule, originally devised by Bean [1994], to construct a permutation representation of the RKs. Genes are sorted in ascending order, thus, providing a permutation of operations. The position with the smallest random key determines the first operation to be sequenced, followed by the position with the second smallest random key, and so on, see part (i) of Figure 3.4.b). This permutation is converted into a feasible sequence of operations by first converting it into the corresponding permutation of jobs (with repetition); thus, each job appears as many times as operations it has, as depicted in Figure 3.4.c). Then job numbers are converted into the corresponding sequence of ordered operations, by replacing (from left to right) the i^{th} appearance of a job by its i^{th} operation, as illustrated in part (i) of Figure 3.4.d).

Each RK in the second part of the chromosome is decoded into the processing speed of the corresponding operation, say l , as $\lceil \text{RK}_l \times |\mathcal{P}_l| \rceil$ - the smallest integer greater than or equal to $\text{RK}_l \times |\mathcal{P}_l|$, where $|\mathcal{P}_l|$ is the cardinality of the set of speed levels for operation $l \in \mathcal{O}$. This is illustrated in Figure 3.4 - part (ii). In this example, all operations can be processed at one of three possible speed levels, i.e., $|\mathcal{P}_l| = 3, l \in \mathcal{O}$. Hence, the first operation (operation 1 of job 1) is processed at speed level $p_1 = 2$ ($\lceil 0.42 \times 3 \rceil = \lceil 1.26 \rceil$), the second operation (operation 2 of job 1) at speed level $p_2 = 3$ ($\lceil 0.81 \times 3 \rceil$), and so on.

Similarly, each RK in the third part is decoded into one of the $|\mathcal{A}|$ vehicles, which is allocated to the transport tasks associated with the corresponding operation, say l , ($\lceil \text{RK}_l \times |\mathcal{A}| \rceil$), and each RK in the fourth and the fifth parts is decoded into one of the $|\mathcal{V}|$ speed levels for, respectively, the empty and loaded transport tasks associated with operation l ($\lceil \text{RK}_l \times |\mathcal{V}| \rceil$). In this example, we consider two vehicles that can travel at one of three speed levels. Thus, task 1 is allocated to vehicle 1 ($a_1 = \lceil 0.12 \times 2 \rceil$), task 2 is allocated to vehicle 1 ($a_2 = \lceil 0.35 \times 2 \rceil$), task 3 is allocated to vehicle 2 ($a_3 = \lceil 0.98 \times 2 \rceil$), and so on. Regarding vehicle traveling speed, the empty and the loaded journey legs of task 1 are traveled at, respectively, $v_1 = \lceil 0.67 \times 3 \rceil = 3$ and $w_1 = \lceil 0.05 \times 3 \rceil = 1$. The traveling speeds for the other tasks are obtained in a similar fashion. Figure 3.4.d) depicts the decoded solution, which is always feasible.

4.3 Crossover Procedure

At each generation, a set of N_o offspring solutions is generated combining the genetic information of two parents. The parents are randomly selected: one from the set of elite solutions

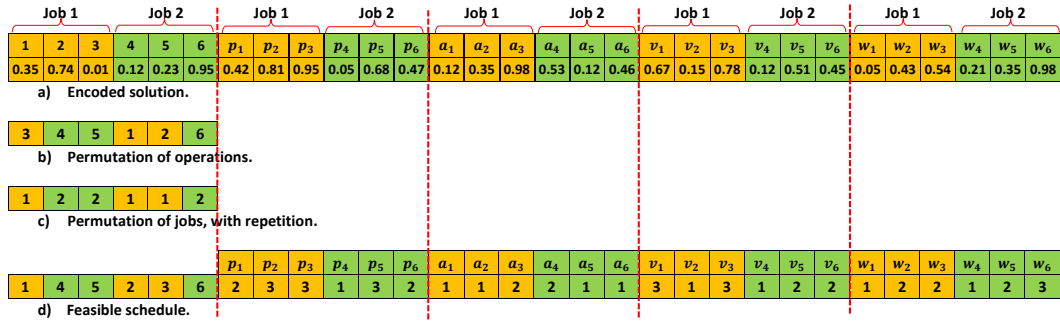


Figure 3.4: Solution encoding and decoding for an example with two jobs, each with three operations that can be processed at one of the three available speed levels, and two vehicles that can travel at one of the three available speed levels (for operation $l \in \mathcal{O}$: p_l - processing speed level, a_l - allocated vehicle, v_l - empty travel speed level, and w_l - loaded travel speed level).

Figure 4 Alt Text: Image illustrating the encoding and decoding of an instance with two jobs, each with three operations that can be processed at one of the three available speed levels, and two vehicles that can travel at one of the three available speed levels.

and the other from the remaining solutions. The recombination is accomplished through a biased parameterized uniform crossover. Bias is introduced in two ways. On the one hand, one of the parents is always chosen from the set of elite solutions and on the other hand, the genes of the elite parent have a larger inheritance probability.

Figure 3.5 illustrates the crossover operator. Figure 3.5 a) and b) show two random-key vectors with 30 genes each. Assume, without loss of generality, that a) refers to the elite parent and b) to the non-elite one. Assume also that each allele of the offspring is inherited from the elite parent with probability $p_e = 0.7$. Finally, let the random inheriting probabilities of the offspring being generated be the ones given by the mapping vector in Figure 3.5.c). The offspring inherits an allele from the elite parent whenever the corresponding element of the mapping vector is smaller than or equal to 0.7. As expected, the offspring resembles the elite parent the most as it inherits most alleles (21 out of 30 alleles) from the elite parent, see Figure 3.5.d).

5 Results & Discussion

Computational experiments were conducted to ascertain the performance of the proposed solution approaches (MILP model and multi-objective mpBRKGA). The performance of the multi-objective mpBRKGA is also compared with that of the Non-dominated Sorting Genetic Algorithm II (NSGA-II). We chose to compare the results of the mpBRKGA with

Part (i): Tasks sequence						Part (ii): Processing speed						Part (iii): Vehicle allocation						Part (iv): Empty travel speed						Part (v): Loaded travel speed							
1	2	3	4	5	6	p_1	p_2	p_3	p_4	p_5	p_6	a_1	a_2	a_3	a_4	a_5	a_6	v_1	v_2	v_3	v_4	v_5	v_6	w_1	w_2	w_3	w_4	w_5	w_6		
0.35	0.74	0.01	0.12	0.23	0.95	0.42	0.81	0.95	0.05	0.68	0.47	0.12	0.35	0.98	0.53	0.12	0.46	0.67	0.15	0.78	0.12	0.51	0.45	0.05	0.43	0.54	0.21	0.35	0.98		
a) Elite parent.																															
1	2	3	4	5	6	p_1	p_2	p_3	p_4	p_5	p_6	a_1	a_2	a_3	a_4	a_5	a_6	v_1	v_2	v_3	v_4	v_5	v_6	w_1	w_2	w_3	w_4	w_5	w_6		
0.03	0.36	0.73	0.74	0.72	0.02	0.08	0.46	0.13	0.62	0.48	0.11	0.75	0.85	0.32	0.41	0.65	0.38	0.19	0.50	0.50	0.30	0.43	0.05	0.43	0.37	0.63	0.25	0.79	0.01		
b) Non-elite parent.																															
0.24	0.69	0.57	0.41	0.39	0.49	0.80	0.42	0.56	0.83	0.17	0.26	0.68	0.75	0.83	0.14	0.29	0.79	0.29	0.49	0.75	0.95	0.03	0.04	0.19	0.02	0.71	0.41	0.93	0.33		
c) Mapping vector.																															
1	2	3	4	5	6	p_1	p_2	p_3	p_4	p_5	p_6	a_1	a_2	a_3	a_4	a_5	a_6	v_1	v_2	v_3	v_4	v_5	v_6	w_1	w_2	w_3	w_4	w_5	w_6		
0.35	0.74	0.01	0.12	0.23	0.95	0.08	0.81	0.95	0.62	0.68	0.47	0.12	0.85	0.32	0.53	0.12	0.38	0.67	0.15	0.50	0.30	0.51	0.45	0.05	0.43	0.63	0.21	0.79	0.98		
d) Offspring.																															

Figure 3.5: Offspring generation example using parameterized uniform crossover with $p_e = 0.7$. In this example, the offspring inherits nine alleles from the non-elite parent (the ones corresponding to the mapping vector elements larger than 0.7) and 21 alleles from the elite parent (the ones corresponding to the mapping vector elements smaller than or equal to 0.7). **Figure 5 Alt Text:** Figure illustrating the offspring generation using parameterized uniform crossover with $p_e = 0.7$. It shows four vectors: the elite parent, the non-elite parent, the mapping vector, and the offspring vector. The offspring has 21 alleles from the elite parent (the ones corresponding to the mapping vector elements smaller than or equal to 0.7) and nine from the non-elite parent (the ones corresponding to the mapping vector elements larger than 0.7).

those of the NSGA-II for three reasons, namely: the NSGA-II fundamental structure is similar and comparable to that of our algorithm; the NSGA-II is one of the most popular multi-objective optimization algorithms; and the NSGA-II is commonly used as a benchmark algorithm to provide baseline results for the evaluation of newly proposed multi-objective optimization algorithms [see, e.g., Zhou and Lei, 2021, Zhang and Chiong, 2016]. The MILP model, the multi-objective mpBRKGA, and the NSGA-II were implemented in Python[®] 3.8 and the MILP model was solved using Gurobi[®] 9.1. All computational experiments were carried out on a 3.20 GHz Intel[®] Core[™] i7-8700 PC with 24 GB RAM.

5.1 Problem Instances

The EEJSPT with speed adjustable machines and speed adjustable vehicles has only been addressed in [Homayouni and Fontes, 2021b], where only two problem instances have been considered. Those problem instances were adapted from the ones proposed in [Yin et al., 2017] for the EEJSP with speed adjustable machines.

Here, we propose 33 problem instances, which are adapted from those proposed in [Yin et al., 2017] and in [Salido et al., 2016] for the EEJSP with speed adjustable machines. The adaptation of these instances requires the specification of the shop-floor layout (randomly

generated) and a limited fleet of identical speed adjustable vehicles (for each instance the number of vehicles is the same as the number of machines)³.

The instances proposed in [Yin et al., 2017] are designated as Yin01, Yin02, and Yin03 and have four, 10, and 20 jobs with 12, 40, and 60 operations, respectively. In instances Yin01 and Yin03 there are five machines to process the operations and in instance Yin02 there are six machines. Machines can be operated at two to three speed levels. All instances proposed in [Salido et al., 2016] consider three jobs and machines that can be operated at one of three speed levels. These instances are designated as Sal01~Sal30: in instances Sal01~Sal10, each job has five operations that are to be processed on three machines, in instances Sal11~Sal20, each job has 10 operations that are to be processed on seven machines, and in instances Sal21~Sal30, each job has 25 operations, that are to be processed on three machines.

Following on Meißner and Massalski [2020], which empirically investigates the energy requirements of automated guided vehicles (AGVs) in a manufacturing shop, we consider vehicles to have three possible traveling speeds, namely: 0.9, 1.2, and 1.5 meters per second (m/s). The corresponding power consumption being 63, 75, and 86 watts per second when traveling empty and 74, 90, and 108 watts per second when traveling loaded. (We assume that every job weighs 48 Kilograms.)

5.2 Experimental Setting

An approximated true Pareto front (PF^*) can be obtained by employing a strategy that combines the “lexicographic” and the ε -constraint methods to solve the MILP model. First, we obtain the extreme solutions of the PF^* by resorting to the lexicographic method. We solve two sequences of two single objective problems, each sequence corresponding to the two possible forms of ordering the objectives, namely: energy first and then makespan and makespan first and energy second. Thus, in the first sequence, we solve a single objective problem optimizing the energy consumption E_0^* and then we solve a single objective problem optimizing the makespan while not exceeding the optimal energy consumption $C^*(E_0^*)$. The other sequence of problems involves optimizing the makespan C_0^* and then the energy consumption subject to the optimal makespan $C^*(E_0^*)$. In the second step, we iteratively solve two single objective problems, one that i) optimizes the makespan with an additional constraint imposing an upper bound on the energy consumption (ε -constraint) and another that ii) optimizes the energy consumption with the additional constraint that the makespan

³ All data pertaining to the problem instances proposed in [Yin et al., 2017] and in [Salido et al., 2016] as well as to the adapted instances can be downloaded from <https://fastmanufacturingproject.wordpress.com/problem-instances>.

cannot exceed the one found in i). At each iteration, the energy consumption upper bound is decreased.

Let C_k^* and $E^*(C_k^*)$ represent the optimal makespan and the optimal energy consumption (subject to the optimal makespan) associated with the single objective problems in i) and ii), respectively. Initially, the energy upper bound (used in (i)) is set to $E^*(C_0^*)$, the optimal energy consumption subject to the optimal makespan, found in the first step. This value is iteratively decreased until it is no longer larger than E_0^* , the minimum energy required (found in the first step). At each iteration k the upper bound on the makespan (used in ii)) is the optimal makespan C_k^* found while solving the problem in i).

For the smaller instances, we were able to obtain a PF^* and thus, the quality of mp-BRKGa and NSGA-II solutions and corresponding Pareto fronts (PFs) are evaluated by comparing them to the PF^* by considering two common performance indicators: on the one hand, we analyse the distance between the PFs and PF^* and on the other hand, we analyse their distribution. For the distance we use the modified Generational Distance (GD^+) and for the distribution we use the Spread (Δ), which, for PFs with n solutions, are calculated as in equations (3.22) and (3.23), respectively [Li and Yao, 2019]:

$$GD^+(PF) = \frac{1}{n} \sum_{i=1}^n \left(\min_{j \in PF^*} \left\{ d_{(i,j)}^+ \right\} \right), \quad (3.22)$$

where $d_{(i,j)}^+ = \sqrt{\left(\max \left\{ C_{max}^i - C_{max}^j, 0 \right\} \right)^2 + \left(\max \left\{ \mathcal{E}^i - \mathcal{E}^j, 0 \right\} \right)^2}$.

$$\Delta(PF) = \frac{d_u + d_b + \sum_{i=1}^{n-1} |d_i - \bar{d}|}{d_u + d_b + \bar{d}(n-1)}, \quad (3.23)$$

where n is the number of solutions in the PF , d_i is the Euclidean distance between the objective function values of two consecutive solutions, $\bar{d}$ is the average over all d_i Euclidean distances, and d_u and d_b are the Euclidean distance between the two extreme solutions of the PF and those of the PF^* , respectively [Fontes and Homayouni, 2022].

The former measures the convergence of the solutions while the latter evaluates their diversity (spread and uniformity). The GD^+ value is to be minimized, zero being the best value as it indicates that the PF found lies on the true Pareto front PF^* . Similarly, a small Δ value is preferred as it is associated with a better PF distribution, both in terms of spread and uniformity. Again, $\Delta = 0$ is the best value since it implies that solutions found are equidistantly spaced and cover the PF^* extremes.

For the larger, instances where a PF^* is not available, we resort to the Hypervolume (HV) [Zitzler et al., 2007] that measures the hypervolume of the space surrounded by the PF and the reference point, which is calculated as in equation (3.24). A larger value of HV indicates better performance regarding diversity and convergence.

$$HV(PF) = VOL\left(\bigcup_{i \in PF} [C_{max}^i, C_{max}^r] \times [\mathcal{E}^i, \mathcal{E}^r]\right), \quad (3.24)$$

where $VOL(\cdot)$ is the Lebesgue measure and $C_{max}^r, \mathcal{E}^r$ are the objective function values of the reference point, which, in this work, are defined as the maximum C_{max} and maximum $\mathcal{E}$ values obtained by either mpBRKGA or NSGA-II.

5.3 Multi-objective mpBRKGA Parameters

The mpBRKGA has several control parameters that need to be tuned.

The mpBRKGA has several control parameters that need to be tuned. An important characteristic of the BRKGAs is the clear division between the problem-independent component (population evolution) and the problem-specific component (decoder). The problem-independent part can be used to implement BRKGAs for many different problems and even to implement different heuristics. Thus, the three parameters associated with the problem-independent part (population evolution) have been set according to literature recommendations as follows: the number of elite solutions to be passed onto the next population was set to 20% of the population ($N_e = 0.2P$), 10% of the population is randomly generated in the same manner as the initial population was ($N_m = 0.1P$), and the probability of inheriting each gene from the elite parent was set to 70% ($p_e = 0.7$) [see, e.g., [Gonçalves and Resende, 2011](#), [Fontes and Gonçalves, 2013](#), [Homayouni et al., 2020](#)].

The remaining control parameters were set through empirical testing on a small subset of five problem instances (Sal01, Sal05, Sal10, Sal15, and Sal20) considering all 600 combinations of the following values: population size $P = \{2N, 5N, 10N, 15N\}$, number of generations $G_{max} = \{100, 200, 300, 400, 500\}$, number of bi-objective populations $\Pi = \{1, 2, 4\}$, number of single objective populations $\Omega = \{0, 2\}$, and number of generations after which the multi-objective populations exchange the best solutions they have found $g_{ex} = \{10, 20, 30, 40, 50\}$. Due to the stochastic nature of metaheuristic algorithms, each of the five instances was solved 10 times for each of the 600 combinations.

Regarding population size, the BRKGA was independently run 10 times for each value ($P = \{2N, 5N, 10N, 15N\}$), and the best solutions and corresponding computation times were recorded. While not much difference was observed for the smaller population sizes ($2N$ and $5N$), we began to observe improvements for the population of $10N$ and even more for the population of $15N$. Although the computation time per generation increases modestly when the population size goes from $2N$ to $5N$, it does increase significantly when it goes from $10N$ to $15N$. Furthermore, for problem instances requiring many generations, larger populations take longer than their small population counterparts to find equally good

solutions. This is clearly due to the better performance achieved by evolving smaller populations over a larger number of generations. A good compromise was obtained by evolving populations with $10N$ individuals over 300 generations. As it can be seen in Figure 3.6, the solutions obtained are diverse and cover, quite uniformly, all objective space of the true Pareto Front (PF^*); thus, providing a Pareto Front (PF) that is a very good approximation, including the extreme points, of the PF^* .

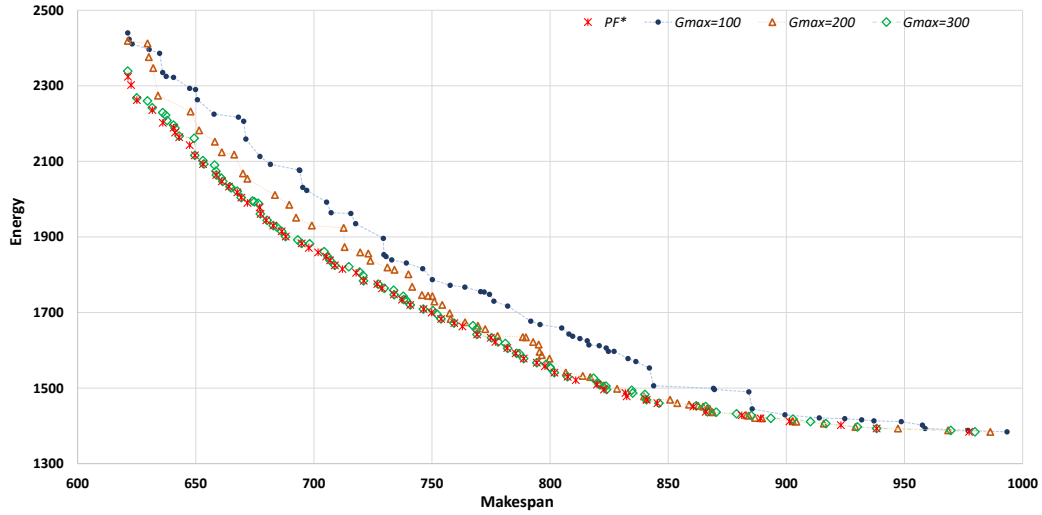


Figure 3.6: Impact of the number of generations on the Pareto front, for problem instance Sal20.

Figure 6 Alt Text: Figure showing four Pareto Fronts to illustrate the impact of the number of multi-objective populations on the quality of the Pareto Front, for problem instance Sal20.

Figure 3.7 illustrates the effect of considering single objective populations. Incorporating the best solutions of the two single-objective populations (i.e., Ω populations) into the bi-objective populations improves the performance of the latter by widening the region of solutions found. By considering the single-objective populations we not only find better extreme solutions, but also find several more solutions in the areas near the boundary solutions. Thus, we have decided to have the two single objective populations, i.e. $\Omega = 2$. The number of multi-objective populations Π also impacts the PIs. Having more such populations leads to better PIs. However, the rate of improvement decreases rapidly as Π increases. A good compromise is obtained for $\Pi = 2$. Figure 3.8 depicts the impact of increasing the number of multi-objective populations on the PF.

Finally, exchanging solutions too frequently or too infrequently degrades the algorithm performance. The best average performance was obtained by exchanging them at about every 30 generations.

In summary, the problem-independent parameters have been set to $N_e = 0.2P$, $N_m =$

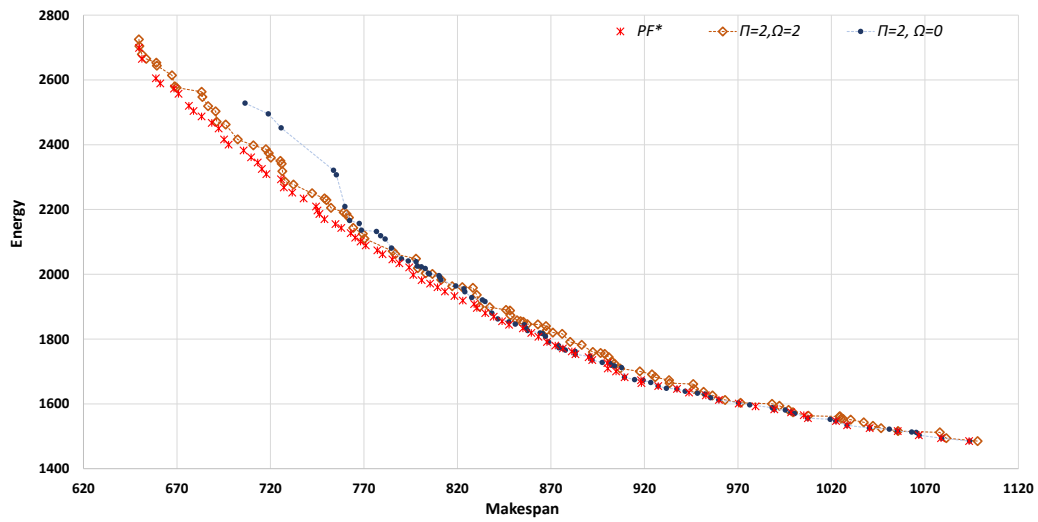


Figure 3.7: Impact of considering the two single objective populations on the Pareto front, for problem instance Sal15.

Figure 7 Alt Text: Figure showing three Pareto Fronts to illustrate the impact of considering two single objective populations on the quality of the Pareto Front, for problem instance Sal15.

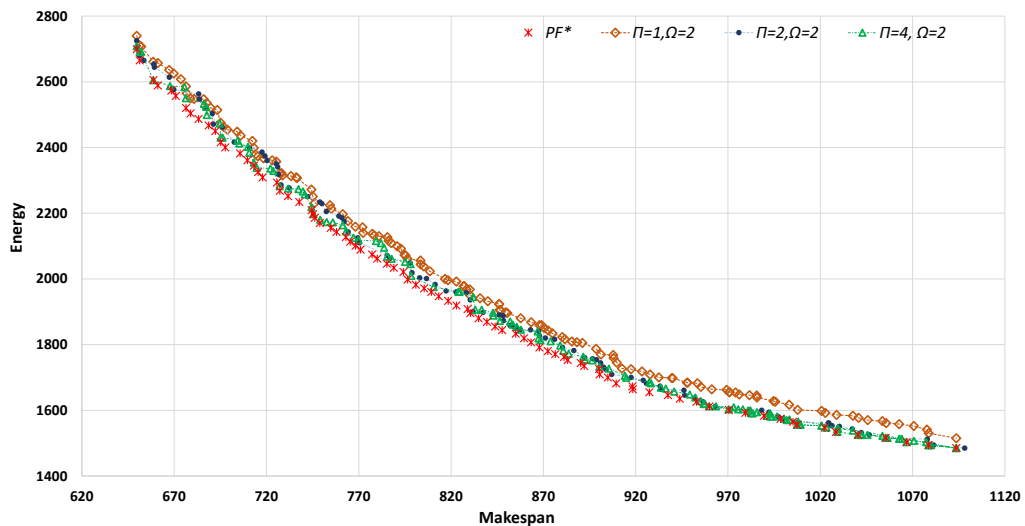


Figure 3.8: Impact of the number of multi-objective populations on the Pareto front, for problem instance Sal15.

Figure 8 Alt Text: Figure showing four Pareto Fronts to illustrate the impact of the number of multi-objective populations on the quality of the Pareto Front, for problem instance Sal15.

$0.1P$, and $p_e = 0.7$ according to literature recommendations, while the problem-dependent ones have been set to $P = 10N$, $G_{max} = 300$, $\Pi = 2$, $\Omega = 2$, and $g_{ex} = 30$ after analyzing the results of the computational experiments performed with a set of instances regarding the performance indicators.

5.4 Computational evaluation

Problem instances Yin01, Yin02, and Sal01~Sal20 were solved by the MILP model using the methodology described in the previous subsection in order to find an approximated true Pareto front PF^* . These instances were also solved using the proposed mpBRKGA and the NSGA-II, 10 times each. Table 3.1 summarizes the results by reporting, for each problem instance, instance characteristics (J - number of jobs, N - total number of operations, and M - number of machines), the optimal makespan C_{max}^* and the optimal energy consumption $\mathcal{E}^*$, obtained by solving single objective MILP models, and the best makespan C_{max} and the best energy consumption $\mathcal{E}$ obtained by the mpBRKGA and by the NSGA-II approaches. It also reports the percentage deviations ($\delta_C = \frac{C_{max} - C_{max}^*}{C_{max}^*} \times 100$ and $\delta_{\mathcal{E}} = \frac{\mathcal{E} - \mathcal{E}^*}{\mathcal{E}^*} \times 100$) between the values of the MILP boundary solutions and those of the mpBRKGA and NSGA-II and the average PI values, over the 10 runs.

As it can be seen from the results reported in Table 3.1, the mpBRKGA found all boundary solutions (two for each problem instance). Moreover, the PF s found by the mpBRKGA closely lie on the true Pareto fronts found by solving the MILP model. This can be seen from the values obtained for the generational distance (GD^+), a convergence measure, that range from 0.002 to 0.026 with an average of 0.008. Furthermore, the mpBRKGA Pareto solutions are uniformly spread over the true Pareto front. Hence, they are diverse and cover most of the Pareto front, including the extreme points. This can be seen from the values obtained for the spread (Δ), a diversity measure (spread and uniformity), that range from 0.309 to 0.658 with an average of 0.456. Additionally, the mpBRKGA outperforms the NSGA-II since both its average generational distance ($\overline{GD^+}$) and its average spread ($\overline{\Delta}$) are lower than those of the NSGA-II.

The MILP model is capable of approximating the true PF of all small-sized instances. However, as expected, this is no longer the case for larger instances, Yin03 and Sal21~Sal30, due to either lack of memory or reaching the 10,000 seconds time limit imposed. For these problem instances, the solutions found by the mpBRKGA are compared with those of a NSGA-II, which is a well established multi-objective metaheuristic that is frequently used to benchmark the performance of other metaheuristics. The results are reported in Table 3.2. For each instance, we report instance characteristics, the best boundary solutions, and the average hypervolume $\overline{HV}$ over the 10 runs for the mpBRKGA and for the NSGA-II. The results clearly show that the mpBRKGA is capable of finding better PFs as the average $\overline{HV}$ is 0.3944 (ranging from 0.0977 to 0.4664) for mpBRKGA and 0.3598 (ranging from 0.0940

Table 3.1: Results for small-sized problem instances: mpBRKGA performance evaluation - comparison with MILP and NSGA-II.

Instances		MILP		mpBRKGA				NSGA-II			
Ins	J-N-M	C_{max}^*	$\mathcal{E}^*$	δ_C	$\delta_{\mathcal{E}}$	$\overline{GD}^+$	$\overline{\Delta}$	δ_C	$\delta_{\mathcal{E}}$	$\overline{GD}^+$	$\overline{\Delta}$
Yin01	4-12-5	25.3	4.86	0.00	0.00	0.002	0.658	0.00	0.00	0.002	0.654
Yin02	10-40-6	43.9	17.89	0.00	0.00	0.026	0.493	0.00	0.00	0.205	0.698
Sal01	3-15-3	39.9	79.0	0.00	0.00	0.015	0.396	0.00	0.00	0.014	0.370
Sal02	3-15-3	55.4	116.1	0.00	0.00	0.011	0.472	0.00	0.00	0.003	0.509
Sal03	3-15-3	45.9	73.1	0.00	0.00	0.006	0.309	0.00	0.00	0.008	0.312
Sal04	3-15-3	45.7	70.1	0.00	0.00	0.008	0.399	0.00	0.00	0.011	0.505
Sal05	3-15-3	41.3	80.1	0.00	0.00	0.003	0.402	0.00	0.00	0.009	0.461
Sal06	3-15-3	47.2	88.1	0.00	0.00	0.007	0.426	0.00	0.00	0.001	0.423
Sal07	3-15-3	46.3	69.1	0.00	0.00	0.013	0.424	0.00	0.00	0.001	0.414
Sal08	3-15-3	45.6	68.1	0.00	0.00	0.005	0.327	0.00	0.00	0.004	0.362
Sal09	3-15-3	54.6	105.1	0.00	0.00	0.003	0.414	0.00	0.00	0.005	0.404
Sal10	3-15-3	56.1	96.1	0.00	0.00	0.009	0.444	0.00	0.00	0.002	0.351
Sal11	3-30-7	664.0	1309.2	0.00	0.00	0.007	0.511	0.00	0.00	0.012	0.657
Sal12	3-30-7	639.4	1542.1	0.00	0.00	0.010	0.478	0.00	0.00	0.032	0.805
Sal13	3-30-7	755.7	2162.1	0.00	0.00	0.009	0.563	0.00	0.00	0.015	0.838
Sal14	3-30-7	551.5	1396.1	0.00	0.00	0.008	0.530	0.00	0.00	0.020	0.799
Sal15	3-30-7	649.7	1485.2	0.00	0.00	0.006	0.368	0.00	0.00	0.008	0.633
Sal16	3-30-7	708.4	1722.2	0.00	0.00	0.004	0.416	0.00	0.00	0.007	0.698
Sal17	3-30-7	600.3	1301.1	0.00	0.00	0.005	0.483	0.00	0.00	0.006	0.616
Sal18	3-30-7	648.9	1818.2	0.00	0.00	0.004	0.498	0.00	0.00	0.017	0.796
Sal19	3-30-7	603.5	1595.1	0.00	0.00	0.011	0.522	0.00	0.00	0.009	0.710
Sal20	3-30-7	621.3	1384.2	0.00	0.00	0.010	0.490	0.00	0.00	0.007	0.654
Mean				0.00	0.0	0.008	0.456	0.00	0.0	0.010	0.566

Table 3.2: Results for large-sized problem instances: mpBRKGA performance evaluation - comparison with NSGA-II.

Instances		mpBRKGA					NSGA-II				
Ins	J-O-M	C_{max}^*	$\mathcal{E}$	C_{max}	$\mathcal{E}^*$	$\overline{HV}$	C_{max}^*	$\mathcal{E}$	C_{max}	$\mathcal{E}^*$	$\overline{HV}$
Yin03	20-60-5	63.1	23.5	112.1	21.3	0.0977	63.1	23.5	112.1	21.4	0.0940
Sal21	3-75-3	1556.8	6078.3	2605.1	3542.3	0.4227	1678.0	6444.3	2586.1	3542.3	0.3832
Sal22	3-75-3	1999.9	7603.4	3210.3	4458.3	0.4148	2133.8	7589.4	3843.3	4458.3	0.3811
Sal23	3-75-3	1702.1	6338.3	3210.8	3469.3	0.4577	1822.3	6299.4	3616.6	3469.3	0.4236
Sal24	3-75-3	1727.1	6466.3	3047.9	3758.3	0.4148	1842.9	6848.4	4364.9	3758.3	0.3887
Sal25	3-75-3	1628.4	6389.3	2794.7	3889.3	0.4012	1731.3	6213.3	3028.7	3889.3	0.3583
Sal26	3-75-3	1556.4	6416.3	1776.1	3739.3	0.4046	1644.6	6072.3	2947.0	3739.3	0.3768
Sal27	3-75-3	1546.0	5938.3	2766.5	3158.3	0.4664	1618.1	5644.4	3196.7	3158.3	0.4304
Sal28	3-75-3	1635.0	6719.3	2889.5	4000.3	0.4143	1761.0	6805.3	3494.4	4000.3	0.3833
Sal29	3-75-3	1837.3	7172.3	3390.2	4056.3	0.4321	1920.1	6997.4	3870.9	4056.3	0.3917
Sal30	3-75-3	1899.0	6791.3	3265.9	4202.3	0.4124	1957.2	6998.3	3662.3	4202.3	0.3472
Mean						0.3944					0.3598

to 0.4304) for the NSGA-II. We also present the best PF found by the mpBRKGA and that found by the NSGA-II for instance Sal25 in Figure 3.9, where the superior performance of mpBRKGA is clearly shown.

5.5 Impact of considering speed adjustable resources and managerial insights

In order to show the positive impacts of considering speed adjustable resources, we have also solved a subset of the problem instances under two additional scenarios in which the machines and the vehicles can only be operated at the highest speed level or at the lowest speed level; thus, having the following three scenarios:

1. scenario $\mathcal{HS}$ - all machines and all vehicles are (always) operated at the highest speed level;
2. scenario $\mathcal{LS}$ - all machines and all vehicles are (always) operated at the lowest speed level;
3. scenario $3\mathcal{S}$ - operating speed levels are chosen for each operation and for each task from the three speed levels available.

Based on these results, some helpful insights are drawn for the managers dealing with such manufacturing settings.

In Table 3.3 we report, for each instance, the minimum makespan C_{max}^* and its corresponding energy consumption $\mathcal{E}$ as well as the minimum energy consumption $\mathcal{E}^*$ and its

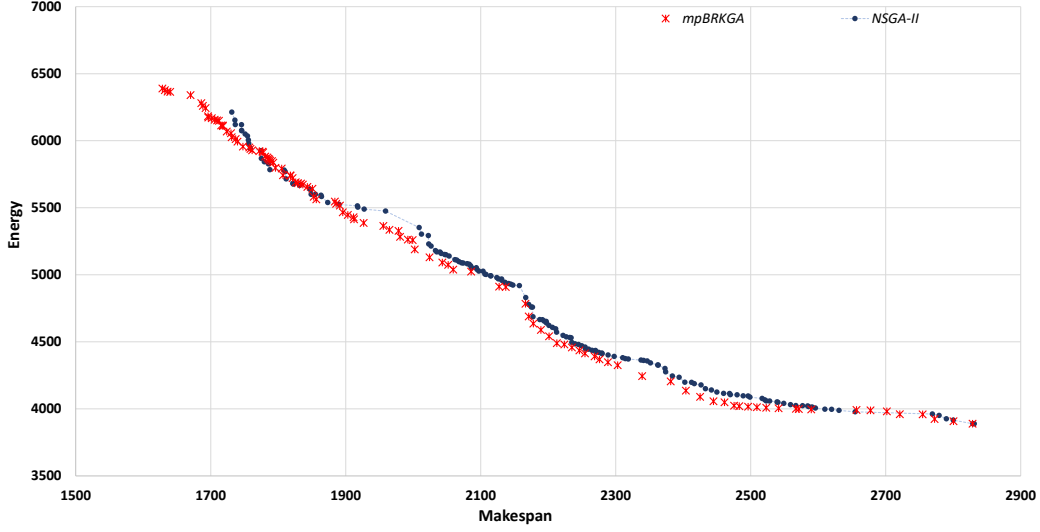


Figure 3.9: The best Pareto Fronts found by the mpBRKGA and by the NSGA-II, for problem instance Sal25.

Figure 9 Alt Text: Figure showing the mpBRKGA and the NSGA-II Pareto Fronts to illustrate the better performance of the mpBRKGA, for problem instance Sal25.

corresponding makespan $C_{\max}$, under the three scenarios. We also report the percentage improvement that can be achieved by the $3\mathcal{S}$ scenario over the other two scenarios as follows:

$$\delta_{C_{\max}^*} = \frac{C_{\max_{3\mathcal{S}}}^* - C_{\max_{\mathcal{HS}}}^*}{C_{\max_{\mathcal{HS}}}^*} \times 100 \text{ and } \delta_{\mathcal{E}} = \frac{\mathcal{E}_{3\mathcal{S}} - \mathcal{E}_{\mathcal{HS}}}{\mathcal{E}_{\mathcal{HS}}} \times 100, \quad (3.25)$$

$$\delta_{C_{\max}} = \frac{C_{\max_{3\mathcal{S}}} - C_{\max_{\mathcal{LS}}}^*}{C_{\max_{\mathcal{LS}}}^*} \times 100 \text{ and } \delta_{\mathcal{E}^*} = \frac{\mathcal{E}_{3\mathcal{S}}^* - \mathcal{E}_{\mathcal{LS}}^*}{\mathcal{E}_{\mathcal{LS}}^*} \times 100. \quad (3.26)$$

As shown, decreasing machine reconfiguration times and increasing the percentage of eligible machine configurations have a considerable positive impact on the performance of the system.

From the results obtained, it is possible to observe that allowing to choose the resources speed settings (considered in the $3\mathcal{S}$ scenario) has a positive impact on the system. It improves on the minimum makespan of the $\mathcal{HS}$ scenario for two instances and obtains the same one for the remaining 10 instances. In addition, the corresponding energy consumption is always lower, on average 10% lower. Note that, for two instances we can improve simultaneously the makespan (about 1% lower) and the corresponding energy consumption (almost 1% and 8% lower). On the other hand, when comparing the results obtained by the $3\mathcal{S}$ scenario with those of the $\mathcal{LS}$ scenario, we can conclude that for five instances the minimum energy consumption is improved (between 0.02% and 11.98% lower) and that the corresponding makespan is always better (between 0.31% and 22.61% lower). These

Table 3.3: Results for a subset of 12 problem instances: improvements achieved by considering speed adjustable resources - comparison with single speed resources.

Ins	$\mathcal{HS}$		$\mathcal{LS}$		$3\mathcal{S}$				GAPs			
	C_{max}^*	$\mathcal{E}$	C_{max}	$\mathcal{E}^*$	C_{max}^*	$\mathcal{E}$	C_{max}	$\mathcal{E}^*$	$\delta_{C_{max}^*}$	$\delta_{\mathcal{E}}$	$\delta_{C_{max}}$	$\delta_{\mathcal{E}^*}$
Yin01	25.3	6.83	39.0	4.93	25.3	5.95	37.2	4.86	0.00	-12.89	-4.47	-1.53
Yin02	43.9	19.55	67.5	20.40	43.9	18.62	52.2	17.96	0.00	-4.76	-22.61	-11.98
Yin03 [†]	63.1	24.31	112.90	22.51	63.1	23.45	112.1	21.27	0.00	-3.53	-0.71	-5.51
Sal01	39.9	133.0	65.8	79.1	39.9	114.0	59.9	79.1	0.00	-14.28	-9.00	0.00
Sal05	41.3	142.0	67.9	80.1	41.3	127.0	62.3	80.1	0.00	-10.56	-8.18	0.00
Sal10	56.1	169.1	88.5	96.1	56.1	148.1	82.5	96.1	0.00	-12.43	-6.86	0.00
Sal11	663.9	2650.2	1099.3	1309.2	663.9	2202.1	1056.0	1309.2	0.00	-16.91	-3.94	0.00
Sal15	649.7	2986.2	1112.8	1485.2	649.7	2699.1	1093.7	1485.2	0.00	-9.61	-1.72	0.00
Sal20	621.3	2568.2	998.6	1384.2	621.3	2324.1	977.3	1384.2	0.00	-9.50	-2.13	0.00
Sal21 [†]	1571.8	6590.3	2758.7	3542.3	1556.8	6078.3	2705.1	3542.3	-0.95	-7.77	-1.94	0.00
Sal25 [†]	1628.4	6908.3	2889.1	3891.3	1628.4	6389.3	2794.7	3889.3	0.00	-7.51	-3.27	-0.05
Sal30 [†]	1916.4	7602.3	3276.0	4203.3	1899.0	6791.3	3265.9	4202.3	-0.91	-10.67	-0.31	-0.02
Mean									-0.16	-10.04	-5.43	-1.59

results contradict common beliefs since energy consumption can be reduced without implying a longer makespan and vice-versa. As a result, managers should pay more attention to the choice of equipment; indeed, resources allowing for speed management can be used not only to decrease the energy consumption or the makespan but also to decrease both simultaneously, as shown in some of the examples.

6 Conclusion

In this work, we address the energy-efficient job shop scheduling problem with transport resources (EEJSPT) in which the operating speed of both machines and vehicles can be adjusted to save time and/or energy. We formulate the problem as a bi-objective Mixed-Integer Linear Programming (MILP) model and propose a solution approach, which combines the “lexicographic” and ε -constraint methods, to approximate the true Pareto front (PF^*). The approach was successfully tested on 22 problem instances with up to 10 jobs, six machines, six vehicles, and 40 operations.

The EEJSPT addressed in this paper is harder than most scheduling problems, since it involves not only scheduling production operations and transport tasks but also allocating each task to a vehicle as well as determining processing and transport speed levels of each operation and each task, respectively. Therefore, we also propose a bi-objective mp-BRKGa that is capable of finding good solutions efficiently. For comparison purposes, we have implemented a Non-dominated Sorting Genetic Algorithm II (NSGA-II) that makes use of the encoding, decoding, and crossover operators we propose for the multi-objective mpBRKGa.

The mpBRKGA finds Pareto fronts (PF) that closely lie on the true Pareto front (PF^*), as the average generational distance is only 0.008, and are well spread and uniformly distributed over the PF^* , as the average spread is only 0.456. Additionally, the mpBRKGA outperforms the NSGA-II since the NSGA-II average generational distance and average spread are, respectively, 0.01 and 0.566. For the set of larger problem instances (with three jobs, 75 operations, and three machines and with 20 jobs, 60 operations, and five machines) the mpBRKGA also outperforms the NSGA-II as the average hyper volume ($\overline{HV}$) is 0.3944 for the former while it is 0.3598 for the latter. Additionally, the mpBRKGA always finds better boundary solutions.

Our experiments show that the use of speed adjustable resources can decrease the energy consumption and/or makespan at almost no extra operational cost. It is shown that by adjusting the speed one can not only reduce the makespan or the energy consumed, but also reduce both simultaneously. On average, the minimum makespan and its associated energy consumption can both be decreased by about 0.2% and 10.0%, respectively. On the other hand, the minimum energy consumption and its associated makespan can be lowered, on average, by about 1.6% and 5.4%, respectively. These values were obtained by considering that all machines and all vehicles are operated at the highest speed level in the former case and at the lowest speed level in the latter. Moreover, adjusting the speed provides management flexibility, since a wider range of trade-off solutions can be found and implemented.

According to the analysis of the impact of considering speed adjustable resources, the following managerial insights can be derived: i) more attention should be paid to employing speed adjustable machines; ii) more attention should be paid to the transport of jobs around the shop-floor, in particular to the transport resources and to the possibility of employing speed adjustable vehicles. A trade-off between budget limits and the benefits of using speed adjustable resources is of utmost importance. Small and medium enterprises (SMEs) could be helped to use energy more efficiently, it would benefit the SMEs by reducing their cost base while simultaneously boosting productivity. Since SMEs globally account for 99% of the business and 60% of employment boosting their productivity amounts to boosting global productivity. However, due to a lack of information, technical expertise and funding, SMEs are rarely able to exploit energy efficiency opportunities resulting in the competitive benefits being lost.

This work can be extended in several ways. Regarding the problem, other characteristics may be considered. For example, including resources that can be switched-off or into a power saving mode while idle, considering other energy factors such as peak-power that usually is a major concern if renewable energies are being used, including other decision-making processes such as maintenance activities, human collaborators, alternative machines, etc. Regarding the approaches in addition to improving the multi-objective mpBRKGA by, for example, embedding a local search procedure, we could also consider

alternative approaches such as simulation and simulation-optimization.

Data availability statement

The data that support the findings of this study are openly available at:
<https://fastmanufacturingproject.wordpress.com/problem-instances>.

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Chapter 4

Conclusions and Future Work

This chapter synthesizes the thesis by explicitly connecting the work developed in Chapters 2 and 3 to the research objectives, research question, and hypothesis stated in Chapter 1. It first highlights the scientific, methodological, infrastructural, and practical contributions of the thesis; it then answers the research question and discusses the limitations and future research directions that follow from the results obtained. The chapter therefore aims not only to close the thesis, but also to make clear how the work advances energy-efficient scheduling for sustainable production and transportation in flexible manufacturing systems.

1 Summary of Contributions

The main contribution of this thesis is not a single model or algorithm in isolation, but the construction of a coherent research path: first, a systematic clarification of the EEJSP literature and its open gaps; second, the definition of a new integrated scheduling problem that combines finite transportation resources with variable machine and vehicle speeds; and third, the development of exact and heuristic solution approaches, together with benchmark instances, for that new problem. This structure responds directly to the jury's observation that the conclusions should foreground the thesis contributions.

This thesis contributes to energy-efficient scheduling research in job shop environments along four complementary dimensions: (i) consolidating and structuring the state of the art (addressing Research Objective 1); (ii) formalizing a novel problem variant that integrates transport scheduling and variable speed settings (addressing Research Objective 2); (iii) developing and validating exact and heuristic solution methods for this variant (addressing Research Objective 2); and (iv) producing publicly available materials- benchmark instances and computational results - to support reproducibility and further research. The contributions of each published article are detailed below, followed by the thesis-level contributions.

Contributions of the literature review (Chapter 2). The first paper surveys 172 papers published between 2013 and 2022 on energy-efficient job shop scheduling and contributes by clarifying terminology, comparing modelling choices, identifying research gaps, and compiling benchmark instances for future work. Its specific contributions are:

- **Clarification of terminology and variant definitions** across the EEJSP and EEJSP literature, reducing the ambiguity that arises from inconsistent naming conventions in earlier studies.
- **Systematic comparison of modelling assumptions, energy-saving strategies, objective functions, and performance metrics**, enabling meaningful cross-study interpretation and revealing the lack of standardized reporting practices.
- **Identification of four major research gaps:** (a) the scarcity of works integrating production and transportation scheduling under energy considerations; (b) the limited treatment of realistic transport constraints, in particular a finite number of vehicles; (c) the rare integration of multiple energy-saving strategies within a single study; and (d) the absence of standardized benchmark instances for several EEJSP extensions.
- **Compilation and publication of benchmark instances** for selected EEJSP variants, providing research infrastructure that supports comparability and reproducibility in future studies.

These contributions directly motivated the problem variant and methods developed in Chapter 3 and are reported in [Fernandes et al. \[2022\]](#).

Contributions of the EEJSPT-VSS study (Chapter 3). The second paper introduces and studies the Energy-Efficient Job Shop Scheduling Problem with Transportation resources and Variable Speed Settings (EEJSPT-VSS), a setting not previously addressed in the literature. Its specific contributions are:

- **Formalization of a novel problem variant (EEJSPT-VSS)** that jointly considers production and transport scheduling under variable speed settings for both machines and vehicles, addressing two of the gaps identified in Chapter 2 within a single integrated formulation.
- **A bi-objective mixed-integer linear programming (MILP) model** for the EEJSPT-VSS, jointly minimizing makespan and total energy consumption, combined with a lexicographic and ϵ -constraint strategy that approximates the true Pareto front for small instances and yields reference solutions for benchmarking heuristic methods.
- **A multi-objective, multi-population BRKGA (mpBRKGA)** tailored to the EEJSPT-VSS. The mpBRKGA produces high-quality, well-distributed approximations of the

Pareto front and outperforms a comparably implemented NSGA-II at a lower computational cost. Its multi-population structure provides a methodological framework that is, in principle, applicable to other multi-objective scheduling problems.

- **Two sets of benchmark instances for the EEJSPT-VSS**, made publicly available so that future works can build directly on the numerical results reported here.
- **Empirical evidence on speed-adjustable resources.** The computational results show that coordinated speed control across machines and vehicles can reduce energy consumption with limited impact on makespan, and that in specific scenarios both objectives can be improved simultaneously. This finding challenges the common assumption of an unavoidable trade-off between energy efficiency and throughput-related performance and supports treating energy and performance as jointly optimizable targets whenever speed control is feasible.

These contributions are reported in [Fontes et al. \[2024\]](#).

Contributions of the thesis as a whole. Considered jointly, the two papers and the surrounding work address the two Research Objectives stated in Chapter 1 and yield the following thesis-level contributions:

- **Scientific contribution.** A structured view of the EEJSP literature (Chapter 2) and a formally defined extension of the EEJSP - the EEJSPT-VSS - that simultaneously integrates transport resources and variable speed settings for machines and vehicles (Chapter 3).
- **Methodological contribution.** An exact bi-objective MILP-based approach and a novel multi-population BRKGA for the EEJSPT-VSS, benchmarked against NSGA-II under a common encoding/decoding framework. The mpBRKGA framework is not specific to the EEJSPT-VSS and may be reused for other multi-objective scheduling problems.
- **Infrastructural contribution.** Publicly available benchmark instances and computational results for the EEJSPT-VSS, supporting reproducibility and direct comparison in future studies.
- **Practical contribution.** Evidence that, in flexible manufacturing systems where machine and vehicle speeds are adjustable, integrated scheduling decisions can reduce energy consumption without reducing (and in some cases while even improving) throughput-related performance. This is directly relevant for sectors that rely on automated or semi-automated transport, such as automotive and electronics manufacturing.

2 Answers to Research Questions

At the outset of this work, a central research question was posed in Chapter 1:

Can energy efficiency and production performance be jointly improved through optimized scheduling in job shop environments with transportation constraints, where both machine operations and vehicle transport tasks can be processed at variable speeds?

The results obtained across this thesis support an affirmative answer. The EEJSPT-VSS study (Chapter 3) shows that simultaneously scheduling production operations and transport tasks under variable speed decisions - at the machine and vehicle levels - enables a systematic exploration of Pareto-optimal trade-offs between makespan and total energy consumption. The reported computational results further indicate that energy savings do not necessarily imply longer makespan, and that in specific scenarios both objectives can be improved jointly. This finding contradicts the common assumption of an unavoidable trade-off between energy efficiency and production performance, and reinforces the value of integrated, speed-aware scheduling decisions.

A more direct answer is therefore: yes, within the problem scope studied in this thesis, energy efficiency and production performance can be jointly optimized. The results show that energy-aware scheduling should not be interpreted only as a trade-off exercise in which energy is reduced at the cost of throughput. When transport operations, vehicle availability, and speed-level decisions are optimized together, the search space contains schedules that reduce total energy consumption with limited makespan deterioration and, in some instances, improve both objectives. This is one of the central substantive findings of the thesis.

Alongside the research question, the thesis also proposed the following hypothesis:

Energy efficiency and production performance can be jointly improved in an EEJSPT environment where machines and vehicles operate at variable speeds, through the development and implementation of appropriate mathematical models and heuristics.

The results obtained in this thesis support this hypothesis. The proposed bi-objective MILP formulation and the mpBRKGA metaheuristic identified schedules that reduced total energy consumption while still achieving strong performance on makespan, and, in specific scenarios, improved both objectives simultaneously. Within the problem scope and benchmark settings considered, these results validate the hypothesis.

Together, the affirmative answer to the research question and the validation of the hypothesis address Research Objective 2 - the development of suitable models and algorithms

for an EEJSP extension that targets identified research gaps - while the systematization carried out in Chapter 2 addresses Research Objective 1 - a structured and critical literature review on EEJSP.

This answer also clarifies the role of the two research objectives. Research Objective 1 is achieved through the systematic review, which identifies the gaps and establishes the need for integrated approaches. Research Objective 2 is achieved through the EEJSPT-VSS model, the exact Pareto-front approximation strategy, the mpBRKGA, and the computational study. The hypothesis is supported because these methods identify schedules that improve energy performance while preserving (and sometimes improving) makespan performance.

3 Limitations

The limitations of the thesis arise mainly from deliberate scoping choices. The work focuses on a novel and already complex integration of production scheduling, limited transport resources, and variable speed settings. This choice made it possible to formulate the problem rigorously and evaluate the proposed solution methods, but it also required excluding some modelling dimensions that would be important in broader industrial applications.

Despite its contributions, this thesis has limitations. Each, however, also points to a concrete opportunity for future research, as detailed in Section 4 :

Scope of energy-saving strategies:

The present work focuses on the integration of variable speed settings (for both machines and transport vehicles) and the joint scheduling of transportation and machine operations. Other energy-saving strategies identified in Chapter 2 were deliberately left out to keep the problem tractable. These include switching machines into sleep or off states during idle periods, considering dynamic (time-of-use) energy pricing, scheduling machine maintenance operations, and allocating workers to machines.

Different industries and production settings may benefit from different combinations of these strategies.

Deterministic assumptions:

The proposed models and algorithms assume a deterministic environment regarding processing times, travel times, energy rates, and machine availability. In practice, manufacturing environments are subject to uncertainties such as machine breakdowns, processing-time variability, and fluctuating energy prices. These were not within the scope of this thesis.

Algorithmic scope:

The empirical comparison was conducted between the proposed mpBRKGA and an NSGA-II implementation sharing the same encoding/decoding framework. Other meta-heuristic families (e.g., large neighborhood search, constraint-programming hybrids, matheuristics, or learning-based methods) were not tested, leaving open the question of whether alternative approaches could outperform the proposed mpBRKGA on the EEJSPT-VSS.

Benchmark instances vs. real production data:

Model and algorithm validation relied on benchmark instances generated under parameter ranges considered reasonable for the problem class. While these instances are useful for controlled comparisons and reproducibility, they may not capture the operational specificities of any particular production environment. Testing the proposed methods on data from an industrial partner would provide complementary evidence of practical applicability.

4 Future Research

Future research should extend the thesis along three main axes: increasing modelling realism, strengthening algorithmic performance, and validating the methods in industrial contexts. The directions below are organized according to these axes and follow directly from the limitations identified above.

The limitations identified in Section 3 each point to a specific avenue for future research. Additional directions, not tied to a single limitation, are also outlined below.

Integration of additional energy-saving strategies

Building on Chapter 2, future work could integrate further energy-saving strategies into the EEJSPT-VSS, such as on/off control during idle periods, dynamic energy pricing, machine maintenance scheduling, or worker allocation. Each of these additions increases problem complexity by introducing new decisions, tracking machine failure rates and reliability, or allocating additional resources. Careful scoping is therefore required to keep the resulting model tractable while improving its realism.

Stochastic and dynamic scheduling

The deterministic assumptions of the current work could be relaxed by developing stochastic, robust, or reactive scheduling methods that explicitly model uncertainty in processing times, travel times, machine availability, or energy prices, or that adapt schedules on the fly in response to disruptions. Such methods would be directly relevant to real-world applicability.

Alternative solution methods

Since the EEJSPT-VSS is newly defined, its algorithmic search space is largely unexplored. Comparing the mpBRKGA with other metaheuristic families (e.g., large neighborhood search, constraint-programming hybrids, matheuristics, or reinforcement-learning-based methods) would provide a clearer picture of which approaches are best suited to this problem and may yield further performance improvements.

Industrial case studies

Applying the proposed models and algorithms to real production data, in collaboration with industrial partners, would complement the benchmark-based validation and help characterize the practical impact of integrated, energy-aware scheduling in concrete operational settings.

Extension to flexible job shop environments (EEFJSP)

This thesis focuses primarily on a Job Shop production setting, specifically the EEJSP, and includes EEFJSP works in the literature review. The EEFJSP is an extension of the Flexible Job Shop Problem (FJSP), a more complex scheduling problem which additionally involves allocating each operation to one of several eligible machines. As discussed in the literature review (Chapter 2), the EEFJSP is still largely unexplored regarding the integration of vehicle scheduling and the joint use of multiple energy-saving strategies. Extending the EEJSPT-VSS to a flexible job shop setting is therefore a natural and potentially relevant direction.

Broader sustainability objectives

The current work targets makespan and total energy consumption. Future studies could broaden the sustainability perspective by incorporating additional objectives such as, for example, carbon emissions, energy cost under dynamic pricing, resource utilization, or waste generation. Handling more than two objectives may require many-objective optimization

techniques or multi-criteria decision-making support.

5 Final Remarks

Manufacturing companies worldwide face mounting pressure to reduce energy consumption and environmental impact without compromising productivity. This thesis contributes to that effort by consolidating the state of the art on energy-efficient job shop scheduling and by addressing one of its main gaps: the joint, energy-aware scheduling of production and transportation under speed-adjustable resources.

The models, algorithms, and benchmark instances developed here support both reproducible research and the design of more energy-conscious scheduling policies in flexible manufacturing systems. The results reported in Chapter 3 indicate that integrated, speed-aware scheduling can reduce energy consumption without sacrificing (and in some scenarios improving) production performance. This suggests that energy efficiency and operational performance are not necessarily competing targets, but can be pursued jointly when the available scheduling decisions are exploited in a coordinated manner. The directions outlined in Section 4 offer concrete paths along which this line of research can be extended toward broader, more realistic, and more industrially relevant settings.

In conclusion, the thesis shows that integrated scheduling can be a practical lever for sustainable manufacturing. By treating production and transportation decisions jointly and by exploiting speed-adjustable resources, manufacturing systems can move beyond isolated machine-level energy savings and toward coordinated operational policies that improve both environmental and production outcomes. This is the main contribution and the main message of the thesis.

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Appendix A

Publications and Communications

The main outputs of the work developed throughout the PhD are presented in this chapter. Two journal papers were published and one additional publication is currently underway, to be submitted to an international journal. Additional publications were submitted to conferences, including a conference paper and two extended abstracts. A poster and a video presentation were also published for one of the journal articles.

Table A.1 provides an overview of all relevant publications, specifying their type, indicating whether they were presented at a conference, reporting their current status, and listing the journal or conference where they were submitted.

Document	Type	Comments	Status	Journal/Conference Name
A	Journal Paper	Thesis chapter 2	Published	Sustainability
B	Journal Paper	Thesis chapter 3	Published	IJPR
C	Journal Paper	-	In Progress	-
D	Conference Paper	Presented in Pilsen, CZ	Published	IEOM'2019
E	Extended Abstract	Presented in Porto, PT	Published	FGP'2022
F	Extended Abstract	Presented in Porto, PT	Published	IEMS'2024
G	Poster	Published in Peeref, 2022	Published	-

Table A.1: Publications produced during this PhD.

1 Main Publications

Publication A: João M.R.C. Fernandes, S. Mahdi Homayouni, Dalila B.M.M. Fontes.
"Energy-Efficient Scheduling in Job Shop Manufacturing Systems: A Literature Review".
In *Sustainability* 2022, 14(10), 6264

Publication B: Dalila B.M.M. Fontes, S. Mahdi Homayouni, João M.R.C. Fernandes.
"Energy-efficient job shop scheduling problem with transport resources considering speed adjustable resources".
In *International Journal of Production Research*, 2024 , Volume 62, Issue 3;
Extended abstract presented at FGP'22 - *French German Portuguese Conference on Optimization 2022*

Publication C: João M.R.C. Fernandes, S. Mahdi Homayouni, Dalila B.M.M. Fontes.
"Energy-efficient Job Shop Scheduling Problem with variable speed settings and machine power-saving modes".
Working Paper;
Extended abstract presented at IEMS'24 - *15th Industrial Engineering and Management Symposium*

2 Additional Publications

2.1 Conference Papers

- **Publication D:** S. Mahdi Homayouni, Amirhossein Khayyambashi, Dalila B.M.M. Fontes, João Chaves Fernandes. "Mathematical Modelling of Multi-Product Ordering in Three-Echelon Supply Chain Networks".

Conference paper published in *Proceedings of the International Conference on Industrial Engineering and Operations Management*. Presented in the same conference, in Pilsen, Czech Republic, July 23-26, 2019

Publication available at:

<https://ieomsociety.org/pilsen2019/papers/363.pdf>

(Included in Appendix B)

2.2 Extended Abstracts

- **Publication E:** João M.R.C. Fernandes, S. Mahdi Homayouni, Dalila B.M.M. Fontes.
"Optimization of Joint Scheduling Speed Adjustable Machines and Vehicles in Job Shops". Porto, Portugal, 2022.

Extended Abstract presented at FGP'22: French German Portuguese Conference on Optimization, Porto, Portugal, May 3-6, 2022

Publication available at:

<https://repositorio-aberto.up.pt/bitstream/10216/141059/2/556902.pdf>

(Included in Appendix C)

- **Publication F:** João M.R.C. Fernandes, S. Mahdi Homayouni, Dalila B.M.M. Fontes. "Energy-efficient Job Shop Scheduling Problem with variable speed settings and machine power-saving modes".

Extended Abstract presented at IEMS '24: 15th Industrial Engineering and Management Symposium, January 2024.

Publication available at:

https://fe.up.pt/degi/iems24/files/Booklet_IEMS24.pdf

(Included in Appendix D)

2.3 Scientific Posters

- **Publication G:** João M.R.C. Fernandes, S. Mahdi Homayouni, Dalila B.M.M. Fontes. "Energy-efficient job shop scheduling problem with transport resources considering speed adjustable resources".

Published in Peeref, in the International Poster Challenger 2023; Entry submitted with a poster and video presentation of the work.

Publication available at:

https://www.peeref.com/poster-competition/202302?action=quick_vote&entry_id=1137

Appendix B

IEOM'19 | Pilsen

Conference paper:

**Proceedings of the International Conference on Industrial
Engineering and Operations Management**

Pilsen, Czech Republic, July 23-26, 2019

Mathematical Modelling of Multi-Product Ordering in Three-Echelon Supply Chain Networks

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Mathematical Modelling of Multi-Product Ordering in Three-Echelon Supply Chain Networks

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Abstract

This paper proposes a mixed integer linear programming model for a multi-product ordering in a three-echelon supply chain network, where multiple manufacturers supply multiple warehouses with multiple products, which in turn distribute the products to the multiple retailers involved. The model considers practical production constraints such as production capacity, backorder allowances, and economically-viable minimum order quantities. Numerical computations show that the model can efficiently solve small-sized problem instances.

Keywords

Supply chain network, Vendor managed inventory, Order quantity, Backorder

1. Introduction

Production systems are under tremendous pressure and face numerous new challenges, such as fluctuation in demand and preferences and rapid changes in technology. They often are part of a larger network, a supply chain network (SCN), integrating material, financial, and information flows.

Supply chain management (SCM) allows for supplying customers in a more efficient and cost-effective way, since a broad range of planning, implementing, and controlling activities required throughout product flow, from the supply of materials to the final product, can be addressed collectively by all parties involved (Zadeh et al., 2014). Decision making in SCM can be categorized into three levels based on the planning horizon (Chopra and Meindl, 2007): strategic, tactical, and operational. Strategic decisions involve long term decisions such as customer segments, product development, logistics infrastructure (manufacturing, warehousing, vendors, etc.), and purchasing; while tactical decisions involve transportation modes, transportation planning, and inventory handling and refer to a time horizon

of a few months. Lastly, at the operational level, daily decisions such as on-hand inventory levels, order quantities, and resources allocation are made. This work addresses operational decisions in a supply chain network.

Recently, both practitioners and scientists have actively contributed to increasing supply chain integration, which not only enhances customers' service level but also decreases costs throughout the whole system. One way of achieving such integration is to define a vendor-managed inventory (VMI) policy under which the supply chain performance can be improved by decreasing inventory-related costs and increasing customer service. VMI is a streamlined approach to inventory management and order fulfilment, in which a downstream body shares its demand information with suppliers and in return benefits from a lower inventory level and a more reliable flow of products. Indeed, in VMI, suppliers decide on the order quantities and their replenishment policies bearing the risk of unfulfilled demands. Figure 1 illustrates the impact of a VMI policy on the decisions made in an SCN. Such a policy can prevent stocking undesired inventories and thus, can lead to an overall cost reduction.

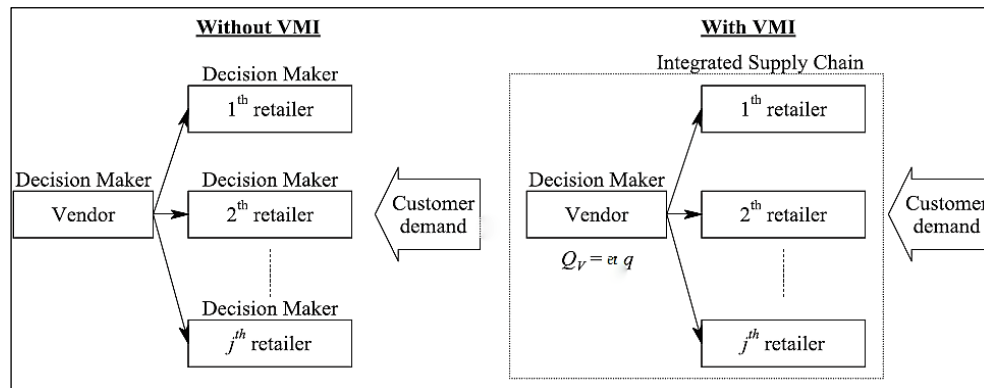


Figure 1. Decision making process with and without VMI policy (Sadeghi et al., 2016).

First VMI's research efforts date back to 1990s, when it has been introduced as an important strategy to decrease *bullwhip effect* in supply chains (Holmstrom, 1998; Waller et al., 1999). Since then, several inventory models under VMI policy have been developed and proposed. For example, Zhang et al. (2007) proposed an integrated cost model for a single vendor that purchases and processes raw materials at a constant production rate and then delivers finished products to multiple buyers, each with a constant demand rate. Buyers may be replenished more than once in a production cycle, possibly having different ordering cycles. The model proposed minimizes the sum of the total costs incurred by the vendor and all the buyers; while finding investment and replenishment decisions for both the vendor and the buyers. Another example is the nonlinear inventory model devised by Darwish and Odah (2010) that minimizes average total cost in a two-echelon SCN involving a single vendor and multiple retailers. The model is solved by finding all Karush–Kuhn–Tucker (KKT) points. The proposed model has been examined in two problem instances; the first one considers five retailers which was used for the sensitivity analysis, the second one, with 30 retailers, was utilized to compare the VMI model with an optimization model without VMI. The VMI model in addition to providing feasible order quantities reduces the total supply chain's cost by 3%; though, it does not necessarily provide the minimum cost for each individual body in the supply chain.

Recently, inventory models under VMI policy have been extended to cope with three-echelon supply chains. Kadavevaramath et al. (2012) propose a mathematical model for a three-echelon SCN (supplier, manufacturer, and distributors) involving the production and distribution of a single product in one planning period that minimizes the total supply chain operating costs, that is purchasing, manufacturing, and transportation costs. The main problem features include demand uncertainty and limited production and supply capacity. Solutions were found by resorting to a particle swarm optimization (PSO) algorithm (in four variants) and a genetic algorithm (GA), for 20 instances obtained by considering one problem instance with two manufacturers and six distributors in 20 different scenarios. Later, Cárdenas-Barrón and Treviño-Garza (2014) proposed an integer linear programming (ILP) model for the three-echelon SCN considered by Kadavevaramath et al. (2012), but extending it, since they consider multiple products and multiple planning periods. They were able to solve optimally the instances generated by Kadavevaramath et al. (2012). However, none of the studies allows for a backorder or considers shipment decisions.

Sadeghi et al. (2013) and Sadeghi et al. (2014) extended the work of Darwish and Odah (2010) by including a central warehouse to where the product is shipped to before being distributed to the retailers. Since the warehouse storage capacity is limited, the product may also be, temporarily, stored at the vendors. Sadeghi et al. (2013) also consider several vendors, and that the annual number of orders received by the warehouse is limited. The problem is formulated as an integer nonlinear programming (INLP) model that while minimizing the total inventory costs of the network (vendors and warehouse) determines the number of orders and orders' quantity received by both the vendors and the warehouse. The authors developed a PSO algorithm, and a GA to obtain approximate solutions for the problem. The authors designed a set of 10 problem instances of different sizes, in which two to five vendors supply up to 20 retailers via a central warehouse. Sadeghi et al. (2014) consider a bi-objective three-echelon SCN involving a single-product, single-manufacturer, single-warehouse, and multi-retailer SCN. The manufacturer produces the product using several machines that work in series. The authors propose an INLP model for which solutions are found by a hybrid bat algorithm. The objectives include minimizing the total supply network costs and maximizing the production machines reliability, which are then aggregated through linear scalarization. Sadeghi et al. (2014) designed a set of 10 problem instance of different sizes, in which a manufacturer with four up to 14 machines produce and distribute a product to three up to 19 retailers via a central warehouse.

More recently, Chan et al. (2016) modelled a three-echelon SCN considering multiple time periods, multiple products, and uncertain demands. Since the main focuses were on enhancing the network's responsiveness (retailers' demand satisfaction within a certain time frame) the main decisions are associated with truck selection and loading sub-problem. The authors consider a multi-objective problem version in which, on the one hand, the costs are minimized (production, transportation, storage, and risk penalty costs) and, on the other hand, the percentage number of times that retailers do not receive their orders in the desired time frame is minimized. Solutions were obtained by using a non-dominated sorting genetic algorithm (NSGA-II) and a heuristic method to determine manufacturer-warehouse allocations, warehouse-retailers allocations, quantities sent from the manufacturers to the warehouses and from them to the retailers, and the trucks of different types needed to transport such quantities. A single instance with 24 time-periods, three manufacturers, five warehouses, eight retailers, 20 products, and 15 truck types was considered.

In this paper, we propose a mixed integer linear programming (MILP) model for a constrained multi-product order quantity under VMI policy in a three-echelon SCN with multiple manufacturers, multiple distributors, and multiple retailers. On the one hand, it extends the model developed by Sadeghi et al. (2013) and Sadeghi et al. (2014) by involving multi-product orders and multiple distributors within the SCN and also by allowing backorder, enforcing production capacity, and imposing upper and lower limits on order quantities; and on the other hand, it extends the model developed by Chan et al. (2016) by allowing backorder, enforcing production capacity, and imposing upper and lower limits on order quantities. A set of small sized-instances is solved optimally as the model proposed was implemented in and solved by the Gurobi® software package. Section 2 defines the specific problem being addressed; while Section 3 formulates the proposed MILP model. Computational experiments and numerical results are reported in Section 4 and some conclusions are drawn in Section 5.

2. Problem Description

The problem described in this section is mainly motivated by a real case, where a holding company within the food industry produces a wide variety of dairy products in its manufacturing plants across the country and distributes them to a wide network of retailers through a set of distribution centres (warehouses). Due to economic reasons, the holding company assumes its manufacturers, warehouses, and retailers to compete among each other and thus, each decides independently on its own costs, prices, and capacities. Nevertheless, decisions for the whole SCN are made under a central inventory management system to gain advantages over competitors. Although the main motivation of the work is a specific food industry supply chain, the problem description and model proposed are general and can be used in any other supply chain with similar specifications.

We consider a three-echelon SCN with a set of manufacturers, a set of distribution centres (warehouses), and a set of retailers; each facility has a known and fixed location. Each manufacturer can produce any of the products, which are then shipped to any of the warehouses, from where the retailers are supplied. Figure 2 depicts a schematic view of such a three-echelon supply chain network. Each retailer has a known constant demand rate for each product within the planning period and can be supplied by one or more warehouses. To supply the retailers, the warehouses order the products from the one or more manufacturers, each of which can produce any or all products.

Although any manufacturer can produce any product, production quantities have lower and upper limits. The lower limits are per product and reflect economic viability; while upper limits are imposed both on each product, reflecting the availability of specific resources or production mix, and on the total production, reflecting production capacity limits (in our case through production time availability). In addition, since products are produced at a constant rate and delivered all at once to the warehouses, for inventory costs purposes we consider the average inventory over the planning period.

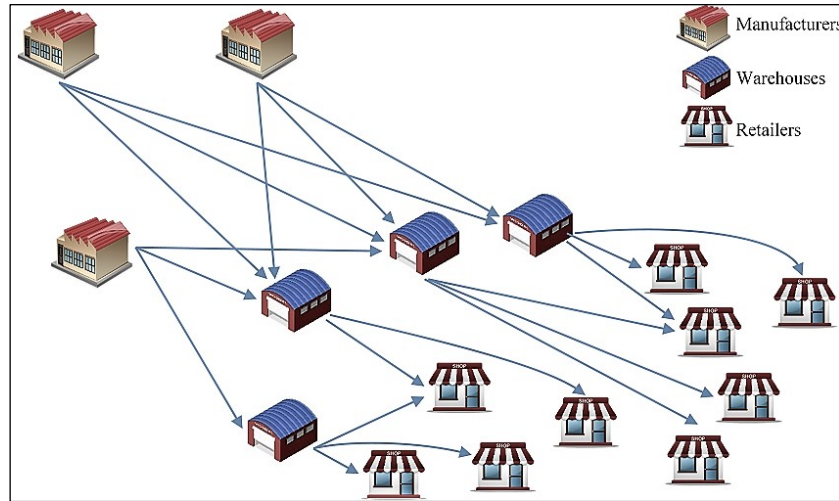


Figure 2. A schematic view of a three-echelon supply chain network

As said before, warehouses buy the products from the manufacturers and since, typically, there is a time difference between their arrival from the manufacturers and their delivery to the retailers, they need to be temporarily stored. Warehouse ordering decisions are bound by storage capacity and budget availability. In here, we consider the total quantity of all products received by a warehouse for the storage capacity and the average inventory over the period for calculating the inventory costs. In addition, warehouses have to comply with a minimum order quantity imposed by manufactures. Retailers place orders for the different products to one or more warehouses and receive them all at once. Since demand occurs at a constant rate throughout the planning period, retailers also have to, temporarily, store the products; again, for cost purposes, we consider the average inventory. In addition, retailers have to comply with a minimum order quantity imposed by warehouses. Backorder is allowed at both the manufacturers and the warehouses; however, it is limited and implies a cost.

Products are transported between manufacturers and warehouses and between warehouses and retailers in vehicles with limited capacity and each manufacturer and warehouse has a fixed and known number of vehicles, all of the same type. Finally, we assume that vehicles do single origin single destination trips only and there is no preexisting backorder.

3. Problem Formulation

This section proposes a mixed linear mathematical programming model to find the quantities of each product that should be i) ordered by each retailer from each warehouse and by each warehouse from each manufacture and ii) backordered by each manufacturer regarding each warehouse order and by each warehouse regarding each retailer order and the number of vehicles each manufacturer and each warehouse need in its fleet to transport the products, at minimum total cost. The costs considered include ordering costs, transportation costs, purchasing costs, holding costs, and backorder costs. Let us first introduce the notation and decision variables used in the MILP model.

Sets and indices:

- M Set of the manufacturers, indexed by $m \in M$;
- W Set of the warehouses, indexed by $w \in W$;

R Set of the retailers, indexed by $r \in R$;
 P Set of the product types, indexed by $p \in P$.

Parameters:

D_{rp} Demand of retailer $r \in R$ for product $p \in P$;
 S_m Fixed ordering cost from manufacturer $m \in M$;
 S'_w Fixed ordering cost from warehouse $w \in W$;
 T_{mw} Fixed transport cost per vehicle dispatched from manufacturer $m \in M$ to warehouse $w \in W$;
 T'_{wr} Fixed transport cost per vehicle dispatched from warehouse $w \in W$ to retailer $r \in R$;
 C_{mp} Marginal purchase cost of product $p \in P$ from manufacturer $m \in M$;
 C'_{wp} Marginal purchase cost of product $p \in P$ from warehouse $w \in W$;
 π_p Marginal backorder cost of product $p \in P$ at the manufacturers;
 π'_p Marginal backorder cost of product $p \in P$ at the warehouses;
 H_{mp} Marginal holding cost of product $p \in P$ at manufacturer $m \in M$;
 H'_{wp} Marginal holding cost of product $p \in P$ at warehouse $w \in W$;
 H''_{rp} Marginal holding cost of product $p \in P$ at retailer $r \in R$;
 L_m Minimum order quantity from manufacturer $m \in M$, regardless of the warehouse;
 L'_w Minimum order quantity from warehouse $w \in W$, regardless of the retailer;
 $\mathcal{L}_{mp}$ Minimum total quantity of product $p \in P$ that needs to be ordered from manufacturer $m \in M$;
 $\mathcal{U}_{mp}$ Maximum total quantity of product $p \in P$ that can be ordered from manufacturer $m \in M$;
 $\mathcal{T}_m$ Production time available (in minutes) for manufacturer $m \in M$ within the planning period;
 β_r Per product percentage backorder allowance limit by retailer $r \in R$, regardless of the product;
 UB_{mp} Maximum backorder units of product $p \in P$ at manufacturer $m \in M$;
 τ_p Production time, per unit, of product $p \in P$, in minutes;
 ω_p Weight, per unit, of product $p \in P$, in Kg;
 ν_p Volume, per unit, of product $p \in P$, in m^3 ;
 C_w Storage capacity of warehouse $w \in W$ in m^3 ;
 B_w Budget available at warehouse $w \in W$ to purchase product(s);
 N_m Available vehicles at manufacturer $m \in M$;
 N'_w Available vehicles at warehouse $w \in W$;
 VC Manufacturers' vehicle capacity (in Kg);
 VC' Warehouses' vehicle capacity (in Kg);
 $\mathcal{M}$ A sufficiently large positive number.

Decision Variables:

Q^p_{mw} Quantity of product $p \in P$ purchased by warehouse $w \in W$ from manufacturer $m \in M$;
 Q'^p_{wr} Quantity of product $p \in P$ purchased by retailer $r \in R$ from warehouse $w \in W$;
 B^p_{mw} Backordered quantity of product $p \in P$ ordered by warehouse $w \in W$ from manufacturer $m \in M$;
 B'^p_{wr} Backordered quantity of product $p \in P$ ordered by retailer $r \in R$ from warehouse $w \in W$;
 V_{mw} Number of vehicles required to transport the products supplied by manufacturer $m \in M$ to warehouse $w \in W$;
 V'_{wr} Number of vehicles required to transport the products supplied by warehouse $w \in W$ to retailer $r \in R$;

X_{mw} Binary auxiliary variable taking the value 1 if manufacturer $m \in M$ supplies, at least partially, warehouse $w \in W$ and 0 otherwise;

Y_{wr} Binary auxiliary variable taking the value 1 if warehouse $w \in W$ supplies, at least partially, retailer $r \in R$ and 0 otherwise;

Z_{mp} Binary auxiliary variable taking the value 1 if manufacturer $m \in M$ produces product $p \in P$ and 0 otherwise.

$$\begin{aligned} \text{Min}Z = & \sum_{m \in M} \sum_{w \in W} X_{mw} S_m + \sum_{w \in W} \sum_{r \in R} Y_{wr} S'_w + \sum_{m \in M} \sum_{w \in W} T_{mw} V_{mw} + \sum_{w \in W} \sum_{r \in R} T'_{wr} V'_{wr} \\ & + \sum_{m \in M} \sum_{w \in W} \sum_{p \in P} C_{mp} Q_{mw}^p + \sum_{w \in W} \sum_{r \in R} \sum_{p \in P} C'_{wp} Q'_{wr}{}^p + \sum_{m \in M} \sum_{w \in W} \sum_{p \in P} \pi_p B_{mw}^p \\ & + \sum_{w \in W} \sum_{r \in R} \sum_{p \in P} \pi'_p B'_{wr}{}^p + \sum_{m \in M} \sum_{w \in W} \sum_{p \in P} H_{mp} \frac{Q_{mw}^p}{2} + \sum_{m \in M} \sum_{w \in W} \sum_{p \in P} H'_{wp} \frac{Q'_{wr}{}^p}{2} \\ & + \sum_{w \in W} \sum_{r \in R} \sum_{p \in P} H''_{rp} \frac{Q'_{wr}{}^p}{2}, \end{aligned} \quad (1)$$

Subject to

$$\sum_{w \in W} (Q'_{wr}{}^p + B'_{wr}{}^p) = D_{rp}, \quad \forall r \in R, p \in P, \quad (2)$$

$$\sum_{r \in R} (Q'_{wr}{}^p + B'_{wr}{}^p) = \sum_{m \in M} (Q_{mw}^p + B_{mw}^p), \quad \forall w \in W, p \in P, \quad (3)$$

$$\sum_{r \in R} Q'_{wr}{}^p \leq \sum_{m \in M} Q_{mw}^p, \quad \forall w \in W, p \in P, \quad (4)$$

$$\sum_{w \in W} B'_{wr}{}^p \leq \beta_r D_{rp}, \quad \forall r \in R, p \in P, \quad (5)$$

$$\sum_{w \in W} B_{mw}^p \leq UB_{mp}, \quad \forall m \in M, p \in P, \quad (6)$$

$$\sum_{p \in P} Q_{mw}^p \geq L_m X_{mw}, \quad \forall m \in M, w \in W, \quad (7)$$

$$\sum_{p \in P} Q'_{wr}{}^p \geq L'_w Y_{wr}, \quad \forall w \in W, r \in R, \quad (8)$$

$$\sum_{p \in P} Q_{mw}^p \leq \mathcal{M} X_{mw}, \quad \forall m \in M, w \in W, \quad (9)$$

$$\sum_{p \in P} Q'_{wr}{}^p \leq \mathcal{M} Y_{wr}, \quad \forall w \in W, r \in R, \quad (10)$$

$$\sum_{w \in W} Q_{mw}^p \geq \mathcal{L}_{mp} Z_{mp}, \quad \forall m \in M, p \in P, \quad (11)$$

$$\sum_{w \in W} Q_{mw}^p \leq \mathcal{U}_{mp} Z_{mp}, \quad \forall m \in M, p \in P, \quad (12)$$

$$\sum_{w \in W} \sum_{p \in P} (Q_{mw}^p \tau_p) \leq \mathcal{T}_m, \quad \forall m \in M, \quad (13)$$

$$\sum_{m \in M} \sum_{p \in P} (Q_{mw}^p C_{mp}) \leq \mathcal{B}_w, \quad \forall w \in W, \quad (14)$$

$$\sum_{m \in M} \sum_{p \in P} (Q_{mw}^p v_p) \leq C_w, \quad \forall w \in W, \quad (15)$$

$$\frac{\sum_{p \in P} (Q_{mw}^p \omega_p)}{VC} \leq V_{mw}, \quad \forall m \in M, w \in W, \quad (16)$$

$$\sum_{w \in W} V_{mw} \leq N_m, \quad \forall m \in M, \quad (17)$$

$$\frac{\sum_{p \in P} (Q_{wr}^p \omega_p)}{VC'} \leq V'_{wr}, \quad \forall w \in W, r \in R, \quad (18)$$

$$\sum_{r \in R} V'_{wr} \leq N'_w, \quad \forall w \in W, \quad (19)$$

$$Q_{mw}^p, Q'_{wr}, B_{mw}^p, B'_{wr}, V_{mw}, V'_{wr} \in \mathbb{Z}_0^+, \quad \forall m \in M, w \in W, r \in R, p \in P, \quad (20)$$

$$X_{mw}, Y_{wr}, Z_{mp} \in \{0,1\}, \quad \forall m \in M, w \in W, r \in R, p \in P. \quad (21)$$

The objective function of the MILP model (1) minimizes the total costs, which comprise i) the fixed costs of ordering from both the manufacturers and the warehouses; ii) the costs of dispatching vehicles from both the manufacturers and the warehouses; iii) the costs of buying the products from both the manufacturers and the warehouses; iv) the backorder costs for both the manufacturers and the warehouses; v) the holding costs incurred at the manufacturers, the warehouses, and the retailers.

Constraints (2) ensure demand satisfaction for all products, either in the current period or at a later period, in the latter case, it is backordered; while constraints (3) ensure that for each warehouse and each product the total quantity, committed and backordered, is the same as the product total quantity received and backordered at the manufacturers. In addition, warehouses cannot supply to the retailers more product than received from the manufacturers, as stated in (4). Service level is ensured by constraints (5) and (6), which limit the backordered quantities as desired.

Minimum order quantities are ensured regarding both the manufactures and the warehouses by constraints (7) and (8), respectively, after ensuring the correctness of the auxiliary variables in constraints (9) and (10), respectively. Three production limits are enforced. On the one hand, a minimum (economic viability) and a maximum (e.g., specific resources availability or production mix) quantity is required for each product, as stated in constraints (11) and (12), respectively. On the other hand, the total production capacity must be satisfied, as stated in (13). Warehouse limits regarding purchasing budget and storage capacity are imposed in (14) and (15), respectively.

The number of required vehicles by each manufacturer to supply each warehouse is determined in (16) the total number of vehicles needed by each manufacturer is ensured to be no more than available ones in (17). Similarly, constraints (18) and (19) ensure the correct number of vehicles for each warehouse. Finally, constraints (20) define the decision variables as non-negative integers and constraints (21) define the auxiliary variables as binary.

4. Computational Experiments

To illustrate the efficiency of the proposed MILP model a set of seven small-sized numerical problem instances were designed. For two of the problem instances (ES1 and ES4), we generated all parameters (i.e., demands, costs, capacities, allowances, and number of available vehicles) randomly. In these two instances, all products can, potentially, be produced by all the manufacturers. Instances ES2 and ES5 have the same characteristics of ES1 and ES4, respectively; however, the values of the cost parameters are 20% higher than those of instances ES1 and ES4, respectively. In contrast, a 20% reduction in the values of the parameters is imposed when generating instances ES3 and ES6, which have the same characteristics of instances ES1 and ES4, respectively. Finally, in instance ES7, which has the same characteristics and parameters as instance ES4, manufacturers are no longer able to produce all products. In fact, each manufacturer can only produce a subset of the products considered.

For ES1, demand of each retailer for each product was randomly generated by a uniform distribution between 400 and 500, marginal purchase costs from the manufacturers were generated randomly by a uniform distribution between 18 and 26, and they were, on average, increased by 5 units for each product purchased from the warehouses; the marginal

backorder costs for the manufacturers and warehouses, for each product, are to be approximately 2 and 3 times the purchasing costs of that product, respectively; the holding costs during the planning period are on average 3.3%, 6.7%, and 10% of the purchasing cost of each product for manufacturers, warehouses and retailers, respectively; and the fixed ordering costs were set to 1000 for each retailer and 500 for each manufacturer. The same methodology was used to generate instance ES4, while the demand of each retailer for each product was generated randomly between 200 and 300, and the purchasing cost from the manufacturers were generated randomly between 18 and 33.

The MILP model was implemented in and solved by Gurobi® software package (Gurobi, 2018), and it was run on a 3.20 GHz Intel® Core™ i7-8700 PC with 24 GB RAM. Table 1 reports the characteristics of the problem instances (number of manufacturers, warehouses, retailers, and products), the optimal supply cost (Z^*), and the computational time in seconds ($Time$) required to find it. The following columns provide the number of nodes and the number of iterations required to solve the instances.

Table 1. Results for the small-sized problem instances.

Instances	Characteristics	Z^*	$Time$	Nodes	Iterations
ES1	3*3*6*3	475,217	0.79	6,169	48,332
ES2	3*3*6*3	570,261	1.04	10,770	68,752
ES3	3*3*6*3	381,574	1.32	12,222	83,165
ES4	3*5*10*4	690,469	12.85	52,268	1,439,579
ES5	3*5*10*4	834,343	7.83	30,814	1,121,098
ES6	3*5*10*4	548,522	6.51	21,181	681,990
ES7	3*5*10*4	811,903	35.07	188,546	7,059,209

Clearly, as the size of the problem increases the time to solve the model also increases. However, from our experiments, it seems that the number of products that manufacturers can produce plays an important role in the required computational time to solve the model. This can be seen from the comparison of the computational times required to find an optimal solution for instances ES7 and ES4; the former being almost a third of the latter. Note that, in instance ES4 each manufacturer can produce any of the four products, while in instance ES7 this figure comes down to three.

Figure 3 illustrates the five main categories of the network's supply costs in instances ES1 to ES7, i.e., total fixed ordering costs (TFC), total transport costs (TTC), total purchasing costs (TPC), total backordering costs (TBC), and total holding costs (THC). On average, 78.4% of the network's supply costs are due to the purchasing costs, followed by 15.9%, 2.2%, 1.8%, and 1.7% of the costs due to holding costs, backorder costs, ordering costs, and transportation costs, respectively.

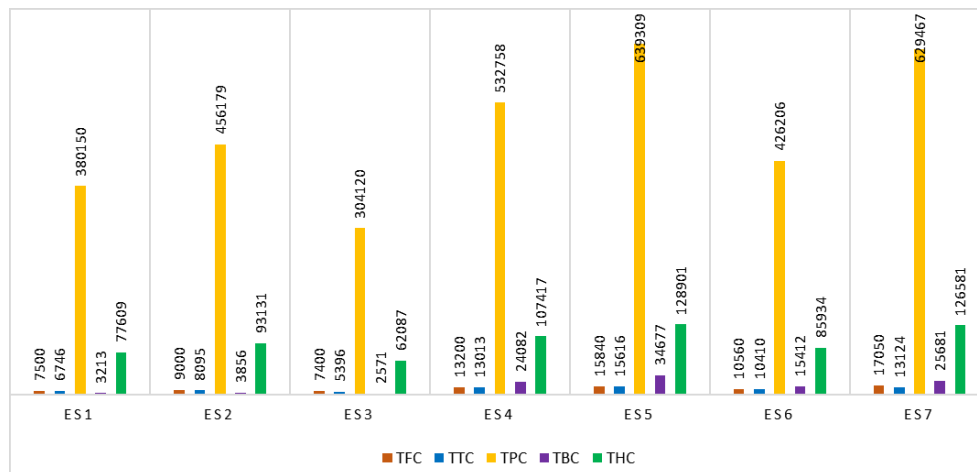


Figure 3. Detailed cost categories in the problem instances

5. Conclusion

This paper introduces a mixed integer linear programming model for the multi-product ordering under the vendor managed inventory policy in a three-echelon SCN. Its novelty comes from the simultaneous optimization of order quantities and number of shipments. Furthermore, the problem considered has features not studied yet in the optimization of such a problem in a three-echelon SCN, such as the allowance of backorder. The computational results obtained show that the proposed modelling approach, in addition to being novel, is capable of quickly finding optimal solutions for small-sized problem instances.

In the near future, we will further our computational experiments and also develop heuristic approaches so that real-sized problem instances can be tackled.

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Biographies

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Appendix C

FGP '22 | Porto

Extended Abstract:

9th French German Portuguese Conference on Optimization 2022

Optimization of Joint Scheduling Speed Adjustable Machines and Vehicles in Job Shops

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Optimization of Joint Scheduling Speed Adjustable Machines and Vehicles in Job Shops

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This work addresses the joint scheduling of speed adjustable machines where the jobs are processed on and vehicles that transport the jobs around the shop floor. It extends the Job shop Scheduling Problem (JSP) [1] and the JSP with Transport resources (JSPT) [2] since in addition to determining, simultaneously, the sequence of the production operations for each machine, the allocation of the transport tasks to vehicles, and the sequence of the transport tasks for each vehicle, one also needs to decide on the processing speed of each production operation and the traveling speed of each task for the empty and for the loaded legs. The most common objective function for the JSP and the JSPT used to be makespan. However, due to extreme weather conditions, stricter environmental regulations, and volatile energy prices energy-efficient scheduling has become a new trend in industry and academia. Particularly, speed adjusting of machines has been extensively practiced to achieve energy-efficient scheduling. The possibility of adjusting the resources working speed is an immediate result of the recent advancements in the Internet of Manufacturing Things (IoMT) in the context of Industry 4.0. At a higher working speed the processing time decreases at the cost of a higher power consumption and vice versa. By adjusting the working speed of some resources one may reduce resources idle time as well as energy consumption without impacting productivity. Recently the energy-efficient JSPT (EEJSPT) under speed adjustment strategy for both machines and vehicles has been considered for the first time in [3] since it attempts to provide the same level of service while consuming less energy. Here, we extend it by proposing a non-dominated sorting genetic algorithm (NSGA-II) that finds effective solutions to the problem efficiently. We also provide a Pareto front analysis to infer on the advantages of considering speed adjusting machines and vehicles.

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Appendix D

IEMS '24 | Porto

Extended Abstract:
15th Industrial Engineering and Management Symposium

Energy-efficient Job Shop Scheduling Problem with variable speed settings and machine power-saving modes

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Energy-efficient Job Shop Scheduling Problem with variable speed settings and machine power-saving modes

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1 The Challenge

Due to a steady increase in both energy demand and environmental awareness, current industry faces added challenges such as stricter regulations and volatile energy costs. To mitigate excess environmental load, research on sustainable manufacturing has been steadily increasing, with a growing number of articles focusing on energy-efficient operation scheduling. Multiple energy-saving strategies have been presented to minimize energy expenditure so far, but are seldom used in conjunction in the same work.

This work focuses on addressing energy efficiency issues in the production process, aiming to find good solutions for scheduling problems in job shop environments, while considering machines with variable speed settings and multiple energy states between operations. This will be achieved by tackling an energy-efficient extension of the Job Shop Scheduling Problem.

The Job shop Scheduling Problem (JSP) is a notoriously difficult combinatorial optimization problem, classified as NP-hard and often used as a comparative testbed for different solution techniques. It is one of the most popular research topics in the areas of operations research and computer science, having been extensively studied for over half a century due to its numerous applications. The JSP is especially relevant in the manufacturing industry, where efficient production scheduling can vastly increase throughput and decrease costs.

In recent years, many works have tackled extensions of JSP with energy considerations. Several authors have referred to the energy-focused extension of JSP as the Energy-efficient Job Shop Scheduling Problem (EEJSP).

The main goal of this work is to incorporate energy consumption into the production scheduling activities of job shop environments. A considerable reduction in energy consumption is expected to be achieved by appropriately i) sequencing production operations for each machine, ii) choosing the machine operation mode (variable speed) and iii) choosing the machine state when not waiting for a job (idle vs. shutdown).

While each of the identified issues has been explored in recent literature by themselves, works tackling all of them in conjunction have not yet had comprehensive research. Thus, an extension of the Energy-efficient Job Shop Scheduling Problem (EEJSP) is proposed which incorporates multiple energy-saving strategies adapted from existing literature. These strategies include turning machines on and off to conserve energy and variable machine operating speeds.

The problem tackled will be bi-objective, simultaneously addressing an economic and an energetic objective function, so as to obtain a set of pareto-optimal solutions, which present the best possible trade-offs between the two objectives, rather than a single solution prioritizing a single objective.

2 The Methodology

In order to tackle the aforementioned problems, two approaches are proposed: mathematical programming modelling and heuristics. Mathematical programming models provide not only a clear mathematical definition of the problem but also exact optimal solutions, which are invaluable when measuring the quality of solutions provided by heuristics. However, their application is limited by their long computation time. To address this shortcoming, heuristic approaches are also developed, which provide good solutions in a much shorter amount of computation time.

The currently envisioned mathematical model will be a mixed-integer linear programming model. Such models contain only linear expressions in both its objective function and constraints and are known

to be provide exact solutions for small problem instances in a reasonable amount of processing time.

Multiple heuristic methods will be tested to solve the proposed novel EEJSP problem, namely, a non-dominated sorting genetic algorithm (NSGA-II) and Biased random key genetic algorithm (BRKGA).

NSGA-II is a well-known multi-objective algorithm proven to work well in many similar EEJSP works. BRKGAs are a variant of Random key genetic algorithms (RKGA) which has also proven to perform well in similar EEJSP problems. Random key genetic algorithms (RKGA) represent a solution to an optimization problem as a vector of random keys (RKs), real numbers in the interval $[0,1]$. This vector is then decoded into a solution to the original problem and its fitness (quality) is calculated. BRKGA consists of an RKGA where one of the parents used for crossover is biased to be of higher fitness than the other parent. An important characteristic of these GAs is the clear division between the problem-independent component (population evolution) and the problem-specific component (decoder), which allows its evolution process to be applied to a variety of problems, so long as a proper decoder is implemented. The decoder uses the indices of the sorted solution vector (comprised of random keys) to represent a feasible sequence. A new generation is obtained from the current one, by copying the best individuals (keeping the best solutions), creating new random individuals (to avoid local entrapment), and producing offspring through biased crossover (keeping good solutions' characteristics). A BRKGA searches the solution space of the problem indirectly, by searching the continuous n -dimensional unit hypercube, using the decoder to map solutions in the hypercube to solutions in the solution space of the problem. For this problem a 3-part single-dimension vector will be used to encode the solution, which will contain the information regarding the operation sequence for the machines, the speed setting for each operation and the machine state after each operation (e.g. idle or shutdown). Furthermore, a model will be used to calculate the optimal starting time for each operation in order to improve the energy consumption for the solutions generated by the BRKGA.

Finally, computational tests for these methods are to be performed on benchmark instances adapted from similar existing EEJSP works.

3 The value to Society

According to the 2021 U.S. Energy Information's International Energy Outlook, the industrial sector - including refining, mining, manufacturing, agriculture, and construction - accounted for more than 50% of end-use energy consumption. Although it dropped by a few percentage points in 2020, due to the effects of the COVID-19 pandemic, energy consumption is projected to surge in 45%, from its current 245 quadrillion British thermal units (BTUs) to over 360 quadrillion BTUs in 2050.

Reducing manufacturing resource expenditure can be achieved through improved machinery, better process/product design or more efficient scheduling. However, comparatively, improving scheduling efficiency requires far less financial investment, making it more widely applicable, especially for small and medium-sized enterprises.

Scheduling is thus one of the success factors of a manufacturing system since it may have a considerable impact on the system performance, both economic and energetic. Energy-efficient scheduling attempts to lower energy consumption while maintaining the same level of service. This reduction can be achieved through improvements such as optimizing machine operation scheduling, machine operating speeds, machine shutdowns and machine ramp-up and ramp-downs. Such improvements not only reduce total energy consumption, but also peak power usage and carbon emissions, as well lowering the total energy costs for the manufacturer. Therefore, the benefits of the application of this research extend not only to the manufacturing entity, but to society as a whole, reinforcing the importance of energy-efficient scheduling.

Regarding scientific knowledge, the contribution of this work to the is twofold: Firstly, new, relevant, and realistic problems are addressed. Solution approaches capable of obtaining good, possibly optimal solutions for Energy-Efficient Job Shop Scheduling Problems will be developed. These approaches differ in their nature (exact and heuristic) and in the way that energy consumption is considered, namely as a cost, and as a trade-off.

Secondly, manufacturers will become aware of better energy resource management strategies, which impact not only the industry, but also society at large. In addition, manufacturers will be given information and computational tools regarding the impacts on energy consumption of simple decisions - such as keeping machines running while waiting to process the next job or shutting them down - that do not require additional investment.

