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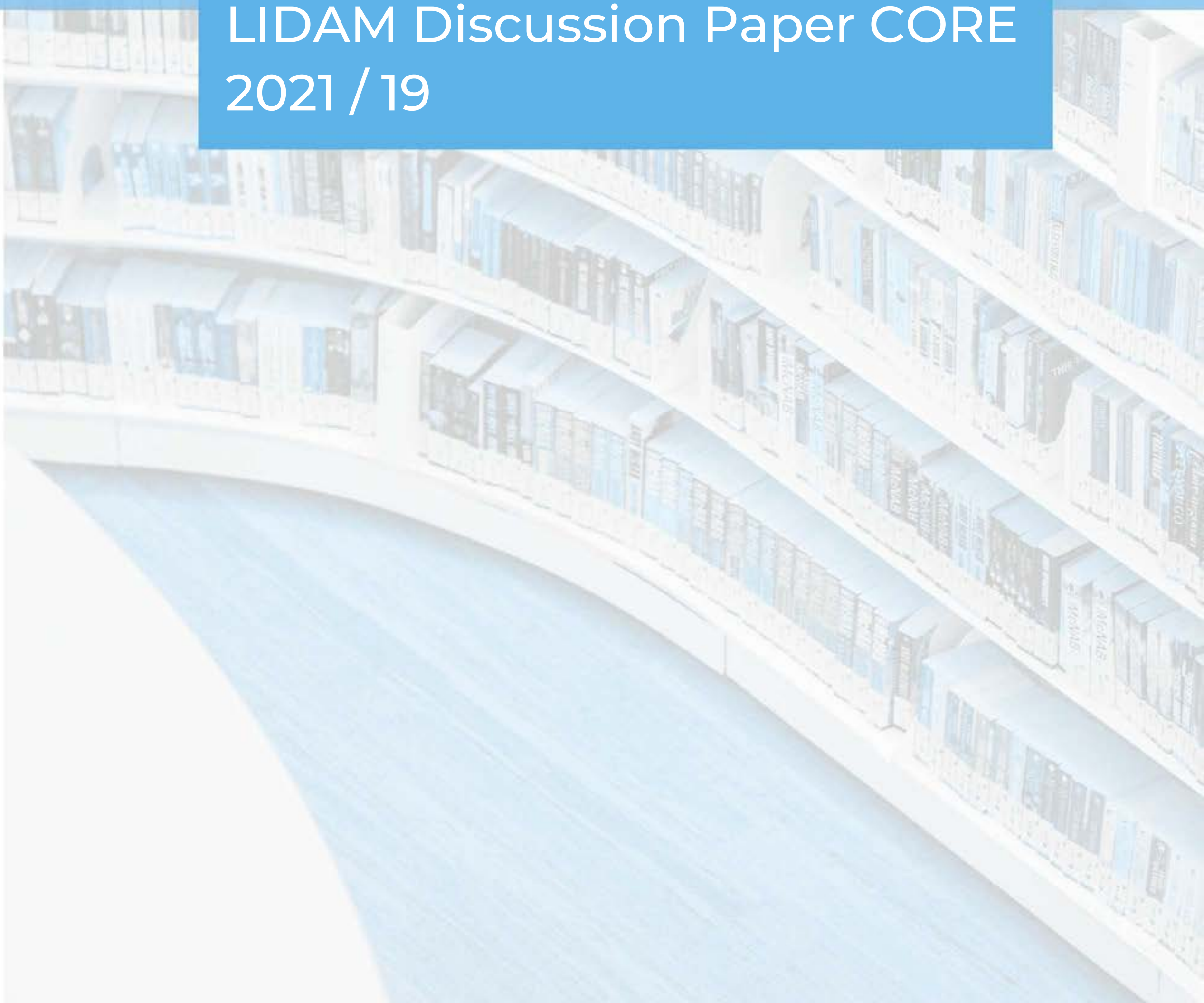

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Job Scheduling under Time-of-Use Energy Tariffs for Sustainable Manufacturing: A Survey

Daniele Catanzaro[a,1], Raffaele Pesenti[b,2] and Roberto Ronco[c,*,3]

[a]Center for Operations Research and Econometrics, Université Catholique de Louvain, Voie du Roman Pays 34, Louvain-la-Neuve 1348, Belgium
[b]Department of Management, University Ca' Foscari, San Giobbe, Cannaregio 837, Venice I-30121, Italy
[c]Department of Informatics, Bioengineering, Robotics and Systems Engineering, University of Genoa, Viale Causa 13, Genova 16145, Italy

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ABSTRACT

The combined increase of energy demand and environmental pollution at a global scale is forcing a rethinking of energy supply policies and production models in sustainable terms. In order to flatten demand peaks in power plants, energy suppliers adopted pricing policies that stimulate a change in the consumption practices of customers. One example of such policies is the *Time-of-Use* (TOU)-based tariffs, which encourage electricity usage at off-peak hours by means of low prices, while penalizing peak hours with higher prices. To avoid a sharp rise of the energy supply costs, manufacturing industry must carefully reschedule the production processes, by shifting them towards less expensive periods. TOU-based tariffs impose specific constraints on the completions of the jobs involved in the production processes as well as a partitioning of the time horizon of the production into a set of time slots, whose associated cost become part of the optimization objective. In this article, we review the flourishing literature on job scheduling in presence of TOU-based energy tariffs. Our purpose is to provide researchers and practitioners with a framework that may guide them towards the most important theoretical results on the topic as well as the most prominent practical applications in sustainable manufacturing.

1. Introduction

The dramatic rise of worldwide energy consumption in the last decades, together with the related environmental pollution, became a compelling matter for global demand supply. The World Energy Outlook 2019 reported 14314 million tonnes of oil-equivalent demand from primary energy consumption, corresponding to 33.2 gigatonnes of CO_2 emission in the sole 2018 [2]. The sectors related to manufacturing, agriculture, mining, and construction collectively consumed 54% of the worldwide energy demand in 2012 [1]. In 2018, the total energy consumption of the sole manufacturing sector amounted to 19.436 trillion British thermal units [37] and, all together, the above sectors were forecast to grow at a rate of 1.2% per year until 2040 [1]. Rethinking the production processes under a sustainable lens, and simultaneously fostering environment-aware consumption practices in customers, appear to be a necessary condition to invert this trend on the long term. One of the first actions undertaken by energy suppliers consisted in flattening the peaks of demand in power plants by means of strategies aimed at reducing the high economic and environmental burdens related to the generation of high energy loads in short periods of time. These strategies mostly consist of pricing policies that stimulate a change in the consumption practices of customers [51]. One example of such policies is provided by the *Time-of-Use* (TOU)-based tariffs, that spur electricity usage at off-peak hours by means of low prices, while penalizing peak hours with higher prices. The identification of the optimal prices with regard to the inherent stochasticity of the demand can be carried out, e.g., by means of robust optimization approaches, such as those described in [51], or stochastic programming models, such as those discussed in [71]. Overall, TOU-based tariff policies proved effective to flatten the peaks of demand so far, by ensuring, at the same time, a good service stability [17, 51]. How long they will succeed to contain a world-scale increase in energy consumption, however, still remain hard to foresee.

*Corresponding author
ORCID(s): 0000-0001-9427-1562 (D. Catanzaro); 0000-0001-5890-4238 (R. Pesenti); 0000-0001-6846-6374 (R. Ronco)
[1]Email: daniele.catanzaro@uclouvain.be (Daniele Catanzaro)
[2]Email: pesenti@unive.it (Raffaele Pesenti)
[3]Email: roberto.ronco@edu.unige.it (Roberto Ronco)

In the context of manufacturing, an immediate and natural reaction to TOU-based tariffs consists in rescheduling the production processes during periods characterized by low energy supply costs. Job scheduling under TOU-based tariffs (or *TOU scheduling* for short) is similar to classical job scheduling problems, in that a processing order of a number of jobs must be identified and carried out on one or possibly multiple machines [76]. The processing of the jobs must comply with time requirements (e.g., a due date or a common deadline) [76]. However, the presence of TOU-based tariffs induces an implicit partitioning of the time horizon of the production into a set of time slots, each associated with a non-negative cost called *TOU costs* [20] or *TOU prices* [35]. This partitioning is usually referred to as *TOU pricing scheme* [19, 35, 85] and the sum of the TOU costs in the considered time horizon, also referred to as *Total Energy Cost* (TEC), becomes part of the classical objectives of a scheduling problem or, in the context of multi-objective optimization problems, adds to the classical *makespan* or the *total weighted tardiness* [76].

The literature on sustainable manufacturing systems offers a number of recent surveys on energy-efficient scheduling. For instance, Gahm et al. [39] study the impact of energy-aware practices in sustainable production and propose a classification of energy-efficient job scheduling based on energetic coverage, energy supply and energy demand. Choudhury et al. [30] focus on the technological aspects of manufacturing, by analyzing the service supply chain and its environmental-related concerns. Despeisse et al. [33] propose a conceptual framework to model single factory units as ecosystems aimed at enabling sustainable performance improvements while limiting environmental pollution and unrestrained exploitation of natural resources. Giret et al. [42] focus on energy-efficiency operations scheduling by exploring the conditions for its sustainability. They distinguish between (i) approaches based on the input data (e.g., as machines, jobs, and scheduling horizon), approaches based on the environmental output (e.g., pollution, waste), and approaches based on mixed objectives. Finally, Gao et al. [40] focus on energy-efficient scheduling in intelligent production systems, by proposing a general classification of the most important problems in sustainable manufacturing and of the corresponding solution approaches. None of the above surveys, however, comprehensively discusses the models, methods, and algorithms for job scheduling under TOU-based energy tariffs presented in the literature. In this article we close this gap, by providing researchers and practitioners with (i) a framework that summarizes the most important theoretical results and practical applications on the topic, and (ii) a guide that may direct new research efforts towards unexplored directions in TOU scheduling for sustainable manufacturing. In Section 2, we shall introduce some notation and definitions aimed at both stating the general TOU scheduling paradigm, and characterizing features that may enable a classification of the different versions of the problem that occur in the literature. We will present a possible classification of these versions in Section 3, by discussing the theoretical and technological motivations at their core as well as the respective approaches proposed to solve them. We will devote Section 4 to a subset of specific versions of TOU scheduling cannot be framed in a standard taxonomy, and that may either guide towards novel research branches or be potentially inspiring in the context of industrial applications. In Section 5, we will finally draw the conclusions, by highlighting the limits of current approaches, and providing future research directions.

2. Notation and problem statement

In this section, we formalize the job scheduling problem in presence of TOU-based energy tariffs.

First, we introduce some notation and definitions that will prove useful in the remainder of the article. Given two positive integers N and K, we denote $\mathcal{J} = \{1, 2, \dots, N\}$ and $\mathcal{T} = \{1, 2, \dots, K\}$ as a set of N jobs to be processed on a single-job processing machine, and a set of K consecutive time slots constituting the time horizon of the production, respectively. We denote p_j as a positive integer encoding the *processing time* of the job $j \in \mathcal{J}$, i.e., the number of time slots required to process j on the given machine. Similarly, we denote the TOU cost associated with the time slot $t \in \mathcal{T}$ as $c_t \in \mathbb{N}$. We refer to the set of the time slots costs c_t, $t = 1, 2, \dots, K$, as $\{c_t\}$ for the sake of brevity. Similarly to Fang et al. [38], we say that $\{c_t\}$ is *pyramidal* if there is some t' such that $c_1 < c_2 < \dots < c_{t'-1} < c_{t'} > c_{t'+1} > \dots > c_{K-1} > c_K$. Moreover, we say that $\{c_t\}$ is *non-decreasing* (respectively, *non-increasing*) if $c_t \leq c_{t'}$ (respectively, $c_t \geq c_{t'}$) for all $t, t' \in \mathcal{T}$, $t < t'$.

We define a *job-time slot assignment* as a pair $(j, \mathcal{T}_j)$ such that j is a job in $\mathcal{J}$, and $\mathcal{T}_j$ is a non-empty subset of p_j time slots in $\mathcal{T}$ during which j is processed. Then, we define a *schedule* S as a set of job-time slot assignments satisfying the following two conditions: (i) exactly one pair $(j, \mathcal{T}_j)$ exists for each $j \in \mathcal{J}$ and (ii) for any pair of distinct jobs $j', j'' \in \mathcal{J}$, the intersection $\mathcal{T}_{j'} \cap \mathcal{T}_{j''}$ is empty, i.e.,

$$S = \{(j, \mathcal{T}_j) : \emptyset \neq \mathcal{T}_j \subseteq \mathcal{T}, \forall\, j \in \mathcal{J}, \text{ and } \mathcal{T}_{j'} \cap \mathcal{T}_{j''} = \emptyset\ \forall\, j', j'' \in \mathcal{J}, j' \neq j''\}. \tag{1}$$

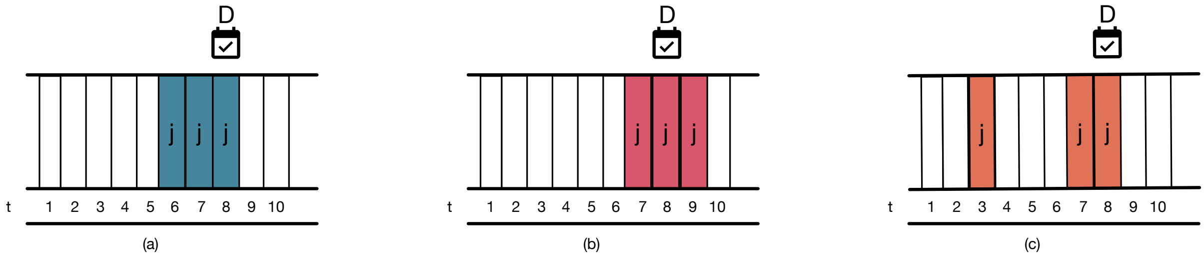

Figure 1: An example of three possible schedules for a dummy instance of the JSTP including a single job j with processing time 3, a time horizon consisting of 10 time slots, a deadline $D = 8$, and TOU costs all equal to one and omitted for the sake of clarity. The schedule shown in Figure 1(a) is non-preemptive while the one shown in Figure 1(c) is preemptive. The schedule shown in Figure 1(a) is feasible as the processing of the job is completed within the deadline. The other two schedules are unfeasible. In particular, the schedule shown in Figure 1(b) violate the deadline and the schedule shown in Figure 1(c) violates non-preemption.

A schedule S is *preemptive* if, for some job $j \in \mathcal{J}$, $\mathcal{T}_j$ contains p_j non-consecutive slots, and *non-preemptive* otherwise. For example, Figure 1 shows three possible schedules for a job j characterized by a processing time $p_j = 3$ over a time horizon of 5 slots. The schedule shown in Figure 1(a) is non-preemptive as job j is processed consecutively during 3 time slots. The schedule shown in Figure 1(c) is instead preemptive, as job j is not processed consecutively during a number of time slots equal to p_j.

We denote $\mathcal{S}$ as the set of the possible schedules of the jobs in $\mathcal{J}$ over the time horizon $\mathcal{T}$, and we define the *Total Energy Cost* (TEC) of a schedule $S \in \mathcal{S}$ as

$$E(S) = \sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}_j} c_t, \tag{2}$$

i.e., as the sum of the TOU costs associated to the job-time slot assignments in S. Similarly, we define the makespan $C_{\max}$ of S as

$$C_{\max}(S) = \max_{t \in \bigcup_{j \in \mathcal{J}} \mathcal{T}_j} t, \tag{3}$$

i.e., as the overall amount of time necessary to process the jobs in $\mathcal{J}$ on the given machine. Then, in the light of the above notation and definitions, we define the basic job scheduling problem in presence of TOU-based tariffs as follows:

Problem : Job Scheduling with TOU tariffs Problem (JSTP).
Given a set of jobs $\mathcal{J}$, a set of processing times $\{p_j\}$ associated with the jobs in $\mathcal{J}$, a time horizon $\mathcal{T}$, a set of TOU costs $\{c_t\}$ associated with the time slots in $\mathcal{T}$, and a positive integer D, called deadline*, find a non-preemptive schedule $S \in \mathcal{S}$ that minimizes the total energy cost* (2) *and whose makespan* (3) *is less than or equal to the given deadline, i.e.,*

$$\min_{S \in \mathcal{S}} \quad E(S) \tag{4}$$

$$s.t. \quad C_{max}(S) \leq D. \tag{5}$$

As an example, by referring again to the three alternative schedules shown in Figure 1, the schedule shown in Figure 1(a) constitutes a feasible solution. The schedule in Figure 1(b), instead, is infeasible as part of job j is processed after the deadline. Similarly, the schedule in Figure 1(c) is not feasible as well because it is preemptive, even if it satisfies the deadline. Figure 2 shows instead an example of a possible schedule for an instance of the JSTP having three jobs $\{i, j, k\}$ with processing times $\{3, 2, 1\}$, a time horizon of 10 time slots, TOU costs $c_t = \{1, 5, 2, 3, 9, 4, 8, 13, 7, 6\}$, and deadline $D = 10$. This schedule has TEC equal to 41 and a makespan of 10. Observe that if job i, j and k were moved to slots $\{2, 3, 4\}$, $\{6, 7\}$ and $\{1\}$, respectively, the resulting schedule would achieve a makespan equal to 7 and a TEC equal to 23, which is provably minimum.

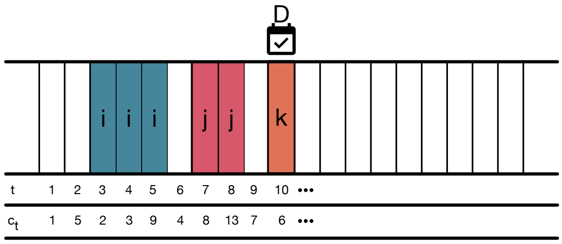

Figure 2: An example of a possible schedule for an instance of the JSTP having three jobs $\{i, j, k\}$, processing times $\{3, 2, 1\}$, a time horizon of 10 time slots, and TOU costs $c_t = \{1, 5, 2, 3, 9, 4, 8, 13, 7, 6\}$. The deadline D here is assumed to be equal to 10.

3. A classification of the literature

In this section, we provide a review of TOU scheduling from an historical perspective. We propose a taxonomy of the literature that, starting from the JSTP, considers problems with more and more specific characterizations of jobs and machines. To this end, we shall make use of Graham et al. [45]'s *three-field* notation, or $\alpha|\beta|\gamma$ notation for short, which is commonly used in job scheduling to describe the problems at hand in a compact and easy-to-read form. The α field characterizes the machines environment. For example, in case of a single machine, α takes value 1, whereas in case of m parallel and identical machines, α is denoted as Pm (where P stands for parallel and identical, and m accounts for the number of considered machines). The β field specifies the constraints and the processing restrictions, such as jobs preemption or release dates, hereafter denoted as prmp and r_j, respectively. Finally, the γ field refers to the objectives to achieve, such as the minimization of the makespan or the TEC. For instance, the JSTP can be represented by means of the three-field notation as $1||TEC$, since it only involves a single machine, and requires to find a non-preemptive schedule that minimizes the TEC. We refer the reader interested in a more in-depth discussion on the three-field notation to Pinedo [76]'s classical book. Here, we just summarize the possible values that the three fields may take in Table 1. We also discuss the development of TOU scheduling for single and multiple machine environments separately, because most of the properties for single machine problems are very hard to generalize to the case of multiple machines. As a matter of fact, only few results in single-machine TOU scheduling directly translate into insights in the context of multiple machine environments. When referring to mathematical programming and algorithms, we shall use the acronyms in Table 2.

Figure 3 and Figure 4 provide historical perspectives on the development of TOU scheduling for single and multiple machine environments, respectively. In what follows, we describe them, by starting from the single-machine TOU scheduling case.

3.1. Single-machine TOU scheduling

The earliest work in single-machine TOU scheduling was proposed by Wan and Qi [90], who investigated five different versions of the TOU scheduling problem differing from one another for the type of considered objective function, namely the total flow time, the maximum lateness, the maximum tardiness, the weighted number of tardy jobs, and the total tardiness. Formally, the authors considered the following five problems: $1||\sum_{j\in\mathcal{J}} C_j + TEC$, $1||L_{\max} + TEC$, $1||T_{\max}+TEC$, $1||\sum_{j\in\mathcal{J}} w_jU_j+TEC$, and $1||\sum_{j\in\mathcal{J}} T_j+TEC$. The authors proved the strong NP-hardness of all the five problems with a reduction from the 3-partition problem. This reduction approach inspired subsequent NP-hardness proofs for further TOU scheduling versions described in [20, 38]. Wan and Qi also proposed polynomial-time algorithms for such five problems under specific assumptions. For instance, let us consider the problem $1||\sum_{j\in\mathcal{J}} C_j + TEC$. First, the authors observed that if the time slot costs $\{c_t\}$ are non-increasing with respect to $t \in \mathcal{T}$, then there is at least an optimal schedule for the problem such that the jobs follow the *Shortest Processing Time first* (SPT) order. The SPT order ensures that, for any two jobs $j, j' \in \mathcal{J}$ with $p_j < p_{j'}$, the processing of job j starts earlier than the one of job j'. Then, by building upon this property, the authors proved that $1||\sum_{j\in\mathcal{J}} C_j + TEC$ is solvable in $O(K^2)$ if the time slot costs $\{c_t\}$ are non-increasing with respect to $t \in \mathcal{T}$. Furthermore, the authors considered the case in which $\{c_t\}$ are contained in the image of some convex non-increasing function. In such a case, for the sake of brevity and with a little abuse of notation, we simply say that the set $\{c_t\}$ is *convex*. The authors proved that, when $\{c_t\}$ is convex, $1||\sum_{j\in\mathcal{J}} C_j + TEC$ is solvable in $O(N^2(N + \log K))$. The authors achieved analogous results for the other four problems. The interested reader may refer to Table 3 for a compendium, and to the original article [90] for a

Field	Characteristic	Meaning
α field	1	single machine
	Pm	m parallel identical machines
	Qm	m parallel machines with different speeds
	Rm	m unrelated parallel machines)
	Fm	flow shop on m machines
	Jm	job shop on m machines
	FFc	flexible flow shop on c machines
	FJc	flexible job shop on c machines
β field	r_j	release dates
	d_j	due dates
	w_j	weights
	prmp	preemption
	batch(b)	batch processing
	prmu	permutation
	q_j	Jobs power demands
	seq	Fixed jobs processing sequence (on a single machine)
	$s_j \in \mathbb{R}_{0+}$	Continuous jobs start time
	on/off	Machines regulation via "on/off" switching mechanism
γ field	$C_{\max}$	makespan
	$L_{\max}$	maximum lateness
	$T_{\max}$	maximum tardiness
	$\sum w_j C_j$	total weighted completion time
	$\sum w_j T_j$	total weighted tardiness
	$\sum w_j U_j$	weighted number of tardy jobs

Table 1
Three-field notation for classical scheduling problems.

complete discussion.

Kulkarni and Munagala [56]'s work constitutes a second earlier example of single-machine TOU scheduling. In this work, the authors considered the problem of finding a preemptive single-machine scheduling including both release dates and jobs weights and involving the minimization of the following objective: $\sum_{j\in\mathcal{J}} w_j(C_j - r_j) + TEC$, that is the weighted sum of the differences between the flow and the release times, plus the TEC. The authors showed that there exists a *Polynomial-Time Approximation Scheme* (PTAS) that allows to approximate the optimal solution up to $(1+\epsilon)$ from the optimal solution, for some $\epsilon > 0$.

Penn and Raviv [75] followed the tracks of Kulkarni and Munagala in proposing a preemptive scheduling problem with release dates. They considered the problem of minimizing the TEC, under the assumption of having a time horizon partitioned into the set of slots $\mathcal{T}$. However, they introduced jobs due dates and relaxed the integrality constraint on the starting times of jobs, by allowing each job $j \in \mathcal{J}$ to start at any time in $[0, K]$. As a result, if some processing occurs during a slot in $t \in \mathcal{T}$, the cost associated with such processing is the whole time slot cost c_t. This assumption characterizes many single-machine TOU scheduling problems in the literature [20, 38]. Penn and Raviv proved that there exists a $O(log_2 K(K + N^2 log_2 K))$ algorithm for $1|\text{prmp}, d_j, r_j|TEC$. Furthermore, the authors showed that there also exists a $O(K \log_2 K + N)$ algorithm for $1|\text{prmp}|TEC$, and they provided an algorithm that solves $1|p_j = 1|TEC$ in $O(K^3)$ time.

Fang et al. [38] enabled another important advancement in the field, by studying problems that consider the jobs power demands $q_j > 0, j \in \mathcal{J}$. From a manufacturing standpoint, the introduction of power demands for jobs reflects the need to model energy-intensive and non-energy-intensive jobs. Formally, if job $j \in \mathcal{J}$ is processed during the time slots in $\mathcal{T}_j \in \mathcal{T}$ on machine h, the cost of processing j is $q_j \sum_{t\in\mathcal{T}_j} c_t$. More generally, if the power demand of job $j \in \mathcal{J}$ also depends on the machine $h \in \mathcal{H}$ that processes j, then the power demand of j is expressed as $q_{j,h} > 0$. Fang et al. considered $1|\text{prmp}, q_j, s_j \in \mathcal{R}_+|TEC$. The authors proved that this problem is easy and that can be solved with a greedy algorithm that exploits the fact that, in an optimal schedule, jobs with a higher power demand are associated with time slots with a lower cost. Fang et al. also studied the problem $1|\text{prmp}, \text{speed}, q_j, s_j \in \mathcal{R}_{0+}, w_j|TEC$, where different parts of a job can be processed at different speeds. In particular, if part of or the whole processing of job $j \in \mathcal{J}$ occurs in some time slot $t \in \mathcal{T}$ at velocity v_t with workload $w_{j,t}$, then the processing time of j in t is $p_{j,t} = w_{j,t}/v_t$, and its power demand is $q_j = v_t^{\delta}$ in t, for some fixed constant $\delta > 0$. The authors provided an explicit expression for the workload and the speed of each job at each $t \in \mathcal{T}$ by formulating the problem as a convex program as well as a polynomial-time algorithm. Rubaiee and Yildirim [79] considered again a preemptive scheduling problem, but they disregarded all the other assumptions introduced by Fang et al. in their scheduling models, in favor of the

Class	Algorithm	Acronym
Mathematical programming and approximation algorithms [55]	Integer Programming	IP
	Linear Programming	LP
	Mixed-Integer Linear Programming	MILP
	Mixed-Integer Non-Linear Programming	MINLP
	Mixed-Integer Programming	MIP
	Polynomial-Time Approximation Scheme	PTAS
Heuristics and metaheuristics [66]	Local Search	LS
	Iterated Local Search	ILS
	Genetic Algorithm	GA
	Evolution Algorithm	EA
	Multi-objective Evolutionary Algorithm based on Decomposition	MOEA/D
	Non-dominated Sorted Genetic Algorithm	NSGA
	Particle Swarm Optimization	PSO
	Tabu Search	TS
	Variable Neighborhood Search	VNS
	Ant Colony Optimization	ACO
	Single-Population Genetic Algorithm	SPGA
	Multi-Population Genetic Algorithm	MPGA
	Strength Pareto-archived Evolutionary Algorithm 2	SPEA

Table 2
Mathematical programming and algorithm acronyms.

the introduction of a second conflicting objective, that is the makespan, along with the TEC. The authors provided a MILP formulation, and an ad-hoc *Ant Colony Optimization* (ACO) implementation to solve the problem. Chen et al. [21] also studied a bi-objective problem, and differently from Rubaiee and Yildirim, that did not consider all the other assumptions introduced by Fang et al., they followed Fang et al.'s footsteps. They studied the problems: $1|\text{prmp}|\sum_{j\in\mathcal{J}} C_j + TEC$, $1|\text{prmp}|\sum_{j\in\mathcal{J}} C_j + TEC$, and $1|\text{prmp, seq}, w_j|\sum_{j\in\mathcal{J}} w_j C_j + TEC$. The authors showed the existence of a polynomial-time algorithm for the first and the second problem, and of a PTAS for the third problem.

Fang et al. also studied the non-preemptive problem $1|\text{speed}, q_j, s_j \in \mathbb{R}_{0+}, w_j|TEC$, where job $j \in \mathcal{J}$ has a processing time $p_j = w_j/v$ and power demand $q_j = v^\delta$ for some fixed $\delta > 0$, being v the processing speed of j. They proved that this problem is NP-hard in the strong sense and provided a $\sum_{k=1}^{K}(c_k \,/\, \min_{t\in\mathcal{T}} c_t)^{\delta//(\delta-1)}$-approximation algorithm. Che et al. [18] considered the similar problem $1|q_j, s_j \in \mathbb{R}_{0+}|TEC$. Che et al. formulated the problem by grouping adjacent time slots with same cost into a same *time period*. This concept frequently occurs in the TOU scheduling literature. As a result, the statement of the problem proposed by Che et al. formally considers a set of time intervals π, with possibly different durations, which partitions the time horizon. The authors proposed a MILP formulation with two different types of assignment variables to handle the condition $s_j \in \mathbb{R}_{0+}$, and they presented a $O(N^2K^2)$ greedy insertion heuristic based on the ideas in the work of Fang et al. [38]. Such a heuristic first sorts the jobs according to the non-increasing order of their power consumption. Then, following such an order, it iterates over each job $j \in \mathcal{J}$, and greedily determines the position for the insertion j.

Again, Chen and Zhang [20] studied $1|s_j \in \mathbb{R}_{0+}|TEC$, and proved its strong NP-hardness with a reduction from the 3-partition problem. The authors provided different polynomial and pseudo-polynomial algorithms based on several assumption on the time slot costs. This work highlights the relations between the structure of $\{c_k\}$ and the existence of efficient solution algorithms. As a remarkable example, Chen and Zhang provided a FPTAS for $1|s_j \in \mathbb{R}_{0+}|TEC$ by exploiting the notion of *valley* for a set of time periods, which is a time interval with a TOU cost lower than its neighbors. Specifically, the authors found that $1|s_j \in \mathbb{R}_{0+}|TEC$ admits a FPTAS when the set of time periods has at most 2 valleys. Table 3 provides a compendium of the results achieved by the authors cited so far.

Some recent took into account multiple objectives in their scheduling models, so as to deal with the conflicting objectives that usually arise in industry settings. One of the first efforts is due to Cheng et al. [26], who developed a bi-objective MILP formulation for the NP-hard problem $1|\text{batch}(b)|C_{\max}, TEC$. This is also one of the first works in single machine batch TOU scheduling. The authors developed an algorithm based on the ϵ-constraint method for multi-objective optimization that is based on solving a sequence of single-objective formulations of the original problems. In [23], Cheng et al. simplified their original MILP formulation [26], and they built a faster optimal ϵ-constraint algorithm upon their results. The blueprint of such an algorithm was further used, developed and refined in subsequent works dealing with bi-objective scheduling [11, 96, 98]. As a specific example, for the same batch scheduling problem tackled by Cheng et al., Wu et al. [98] proposed two new fast ϵ-constraint-based constructive heuristics that improve Cheng et al.'s algorithm from a computational standpoint. Zhou et al. [113] also considered a batch scheduling problem with

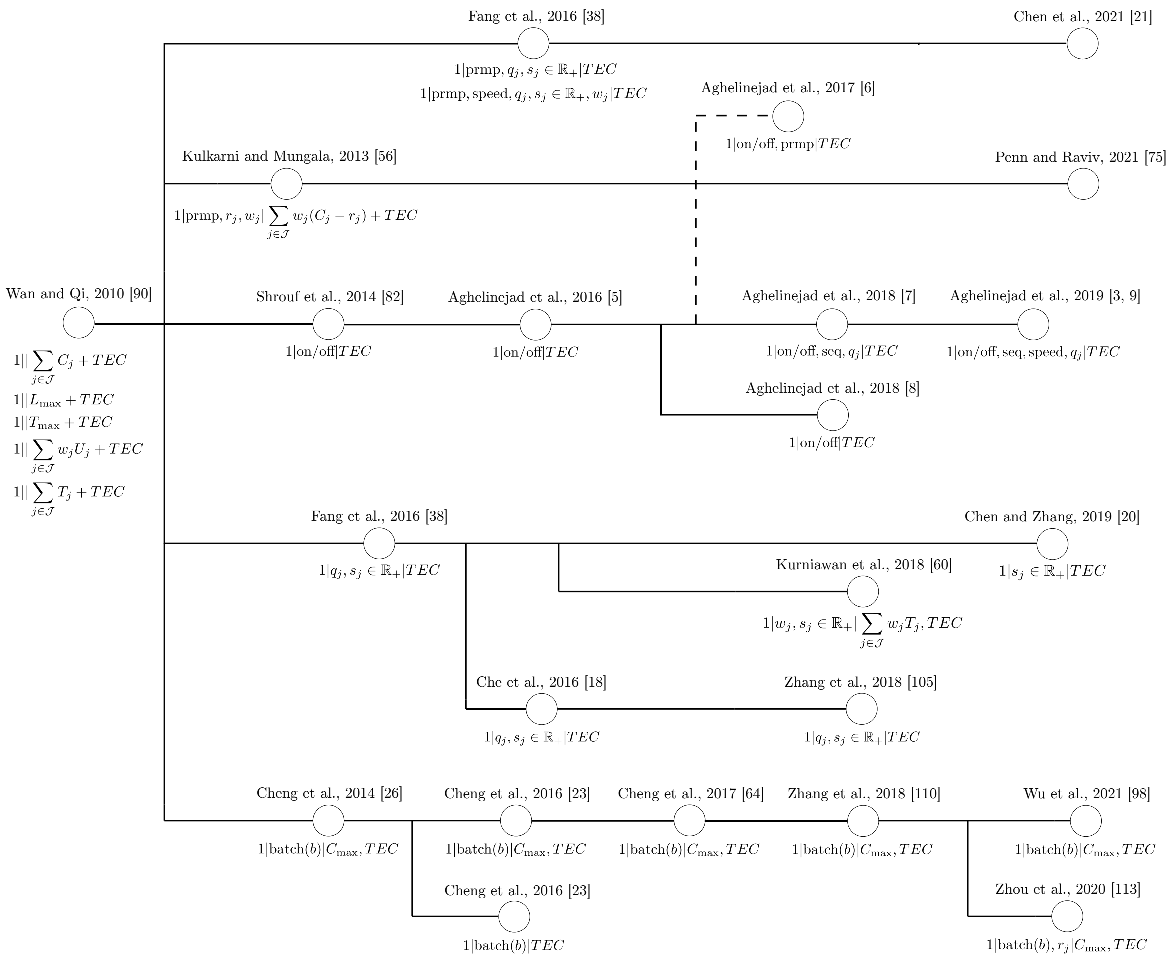

Figure 3: Historical development of TOU scheduling for single machine environments.

release dates inspired by the main research stream in single machine batch scheduling initiated by Cheng et al.. This problem has again multiple objectives, as it requires the simultaneous minimization of the makespan and TEC. Finally, the work of Cheng et al. [25] stands out as one of the few efforts in single machine batch TOU scheduling, as it considers a single objective. Cheng et al. presented and compared two different MILP formulations for $1|\text{batch}(b)|TEC$.

A particular niche of the literature considers also the possibility of switching the machines on and off, according to the so-called "on/off" mechanism. Within such a setting, a machine can be in one of these three states: (a) "processing", (b) "idle", or (c) "shutdown". A machine in state (b) requires energy despite not processing any job, but is ready to start processing a job at any time. A machine in state (c) is instead shut down, i.e., it is "off". Its energy consumption is zero, but it cannot process any job without first transitioning into state (a). However, in order to do so, a machine requires a certain amount of time and energy. Shrouf et al. [82] were the first authors to study $1|\text{on/off}|TEC$ as well as to provide a MILP formulation and a GA for the problem. Their industry-oriented model was a milestone for the formalization of the "on/off" switching mechanism in TOU scheduling. Aghelinejad et al. also studied $1|\text{on/off}|TEC$: by building upon Shrouf et al.'s effort, they provided an improved MILP formulation [5] that they later strengthened with further lower bounds [3]. Aghelinejad et al. also developed a heuristic and a GA for the problem in [8]. Aghelinejad et al. also considered the preemptive version of $1|\text{on/off}|TEC$, i.e., $1|\text{on/off}, \text{prmp}|TEC$ [6]. This assumption enabled the development of a polynomial-time solution algorithm based on dynamic programming for the problem. The idea at the core of such an algorithm is to represent the total order of the slots in $\mathcal{T}$ by means of a directed graph, which reduces the scheduling problem to a shortest path problem. In a subsequent work, Aghelinejad et al. introduced the assumption of the fixed jobs sequence [3, 9]. In such a case, the jobs in $\mathcal{J}$ are constrained to follow a specific processing

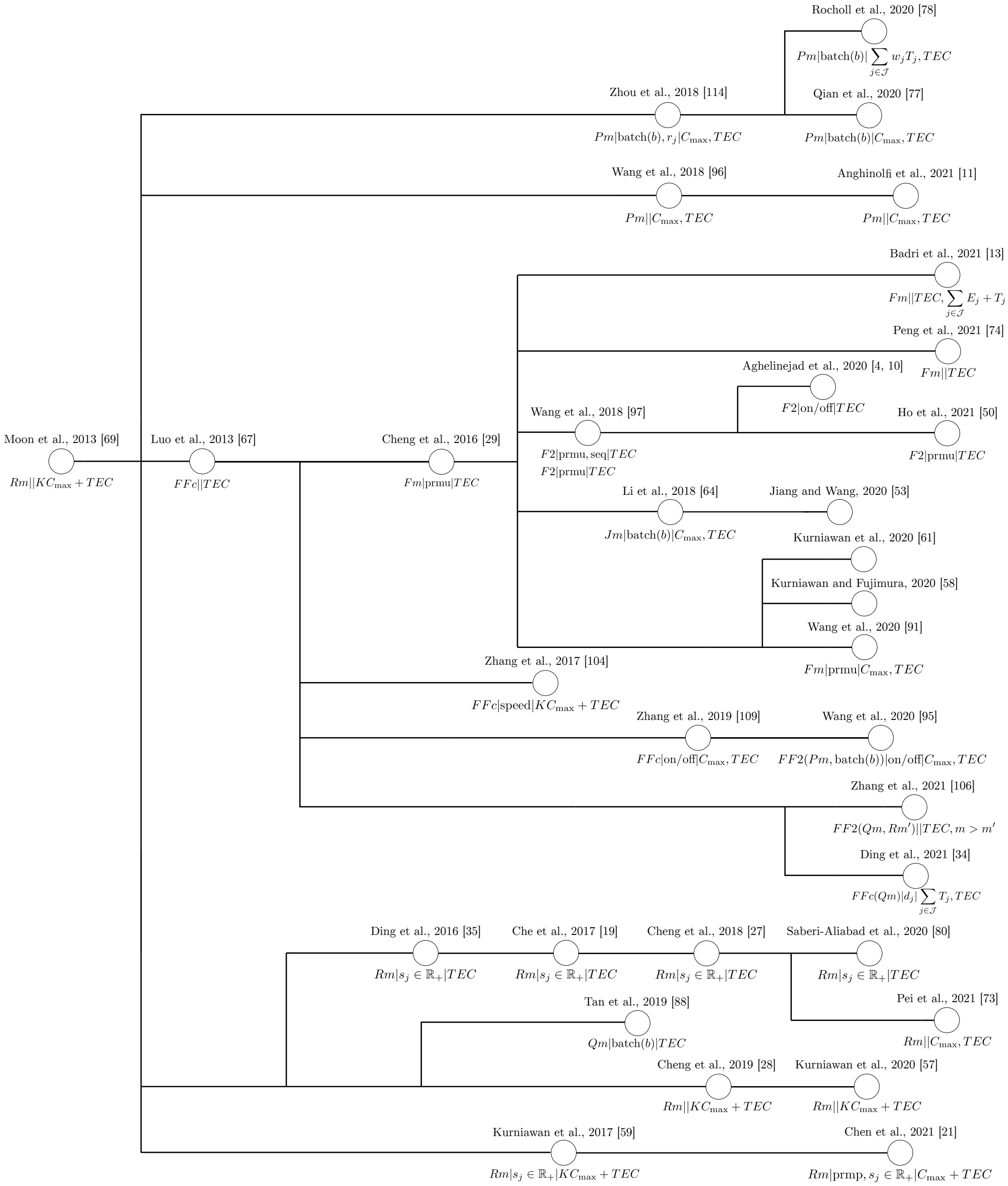

Figure 4: Historical development of TOU scheduling for multiple machine environments.

sequence on the single machine, which induces a total ordering on the start times of the jobs in $\mathcal{J}$. We denote a fixed processing sequence with seq in the β field of the three-field notation. It is interesting to observe that some TOU scheduling problems with such a total ordering can be solved to optimality in polynomial [3, 9] or pseudo-polynomial [7] time. Specifically, in [3, 9], Aghelinejad et al. developed a $O(K^3)$ algorithm for $1|\text{on/off, seq}, q_j|TEC$ by adapting the idea at the core of the dynamic programming algorithm used for $1|\text{on/off, prmp}|TEC$ [6]. Instead, in [7], Aghelinejad et al. further extended their work by considering the power demands of the jobs in a speed-scalable version of the problem. Formally, the authors considered $1|\text{on/off, speed, seq}, q_j|TEC$, and they again adapted the dynamic programming algorithm proposed in [6]. Such an algorithm attains a $O(K^2V(K+V))$ worst-case complexity, where V is the number of distinct processing speeds of the machine.

Article	Problem	Computational complexity of the solution algorithm	Assumptions
Wan and Qi [90]	$1\|\|\sum_{j\in\mathcal{J}} C_j + TEC$	$O(K^2)$ $O(N(N^2+\log\{K\}))$	$\{c_k\}$ non-increasing $\{c_k\}$ convex non-increasing
	$1\|\|L_{\max} + TEC$	$O(K^2)$ $O(K\log K)$	$\{c_k\}$ non-increasing $\{c_k\}$ convex non-increasing
	$1\|\|T_{\max} + TEC$	$O(K^2)$ $O(K\log K)$	$\{c_k\}$ non-increasing $\{c_k\}$ convex non-increasing
	$1\|\|\sum_{j\in\mathcal{J}} w_jU_j + TEC$	(a) $O(K^2)$ or (b) $O(NK^3)$	tardy jobs as (a) lost sales or (b) backlogging
	$1\|\|\sum_{j\in\mathcal{J}} T_j + TEC$	$O(N^4K^3)$	$\{c_k\}$ monotone non-increasing
Fang et al. [38]	$1\|\text{prmp}, q_j, s_j \in \mathbb{R}_{0+}\|TEC$ $1\|q_j, s_j \in \mathbb{R}_{0+}\|TEC$ $1\|\text{prmp}, \text{speed}, q_j, s_j \in \mathbb{R}_{0+}, w_j\|TEC$	No explicit expression. No explicit expression. No explicit expression.	$\{c_k\}$ pyramidal
Chen and Zhang [20]	$1\|s_j \in \mathbb{R}_{0+}\|TEC$	$O(\|\pi\|)$ $O((\sum_{j\in\mathcal{J}} p_j)^v(N+\|\pi\|^v))$ $O(\|\pi\|^2N^{2r-1})$ $O(\|\pi\|(\|\pi\|+N)N^3)$ $O(\|\pi\|^{\pi+2}N^{3\|\pi\|-1})$	π has 1 valley π has $v\geq 2$ valley π has 2 valleys, $\|\mathcal{P}_{\mathcal{J}}\| = r$ Bounded lateness, π has 1 valley $\sum_{j\in\mathcal{J}} p_j$ bounded; π has 1 valley
Chen et al. [21]	$1\|\text{prmp}\|\sum_{j\in\mathcal{J}} C_j + TEC$ $1\|\text{prmp}, \text{seq}, w_j\|\sum_{j\in\mathcal{J}} w_jC_j + TEC$	No explicit expression. $O(NK)$	
Penn and Raviv [75]	$1\|\text{prmp}, d_j, r_j\|TEC$	$O(log_2K(K+N^2log_2K))$	
Aghelinejad et al. [6]	$1\|\text{on/off}, \text{prmp}\|TEC$	$O(K^3)$	
Aghelinejad et al. [3, 9]	$1\|\text{on/off}, \text{seq}\|TEC$	$O(K^3)$	
Aghelinejad et al. [7]	$1\|\text{on/off}, \text{seq}, q_j\|TEC$ $1\|\text{on/off}, \text{speed}, \text{seq}, q_j\|TEC$	$O(K^3)$ $O(K^2V(K+V)),\ V\in\mathbb{Z}_+$	
Wang et al. [97]	$F2\|\text{prmu}, \text{seq}\|TEC$	$O(NK^4)$	

Table 3
Optimal polynomial and pseudo-polynomial time algorithms for different TOU scheduling problems.

3.2. Multiple-machines TOU scheduling

Some TOU scheduling problems generalize the JSTP by considering multiple machines [11, 35]. In such problems, each job $j \in \mathcal{J}$ has to be scheduled in a subset $\mathcal{T}_j \subseteq \mathcal{T}$ on a machine h_j in a set $\mathcal{H} = \{1, 2, \dots, M\}$ of machines so as to minimize the total energy consumption. For each $j, j' \in \mathcal{J}$, then $\mathcal{T}_j \cap \mathcal{T}_{j'} = \emptyset$ only if j and j' are scheduled on the same machine $h_j = h_{j'}$.

A schedule for TOU scheduling problems with multiple machines can be generalized from (1) as follows. We define a *job-machine-time slot assignment* as a triplet $(j, h_j, \mathcal{T}_j)$ such that j is a job in $\mathcal{J}$, h_j is a machine in $\mathcal{H}$, and $\mathcal{T}_j$ is a non-empty subset of p_j time slots in $\mathcal{T}$ during which j is processed on h_j. Then, we define a schedule S on multiple machines as

$$S = \{(j, h_j, \mathcal{T}_j) : \mathcal{T}_j \subseteq \mathcal{T}, \forall\, j \in \mathcal{J}, \text{ and } \mathcal{T}_{j'} \cap \mathcal{T}_{j''} = \emptyset\ \forall\, j', j'' \in \mathcal{J}, j' \neq j'', h_j = h_{j'}\}. \tag{6}$$

Each machine $h \in \mathcal{H}$ is generally associated with a positive energy consumption rate u_h. The energy consumption rate reflects into the energy cost of the scheduled jobs. In particular, if job $j \in \mathcal{J}$ is scheduled in $\mathcal{T}_j$ on machine $h_j \in \mathcal{H}$, the cost associated with the processing of the job j is $u_{h_j}\sum_{k\in\mathcal{T}_j} c_k$. Consequently, we can generalize the TEC of a parallel machines schedule as

$$E(S) = \sum_{j\in\mathcal{J}} u_{h_j} \sum_{t\in\mathcal{T}_j} c_t. \tag{7}$$

Trivially, (6) and (7) reduce to (1) and (2), respectively, if $\mathcal{H} = \{1\}$ and $u_1 = 1$.

One of the early studies in TOU scheduling with multiple machines is due to Moon et al. [69] that, inspired by the practical problems of South Korean electricity industries, considered $Rm||KC_{\max} + TEC$ for the first time. Moon et al. formulated the problem as MILP program. However, they were unable to experimentally evaluate it with a commercial MILP solver due to the high computational burden. For this reason, the authors developed a Hybrid GA with far lower running times. In this way, the authors had an algorithm that could solve their benchmark instances built from real data. The problem proposed by the authors opened the way for several researchers on the topic. Indeed, Cheng et al. [28]

expanded Moon et al.'s work by improving their model, so as to enable the development of a computational approach that solves $Rm||KC_{\max} + TEC$ Moon et al.'s benchmark instances to optimality within a reasonable time. Moreover, Kurniawan et al. [57] pursued the search for an effective metaheuristic algorithm for the problem, by proposing a GA that builds upon Moon et al.'s design. In [59], Kurniawan et al. instead relaxed the integrality of the start times by considering $Rm|s_j \in \mathbb{R}_{0+}|KC_{\max} + TEC$ which they again faced with a GA. Following this line, Chen et al. [21] studied $Rm|\text{prmp}, s_j \in \mathbb{R}_{0+}|C_{\max} + TEC$, and they showed that the the preemption assumption allows to develop an algorithm which runs in $O(K^2)$ time, plus the time required to solve $Rm|\text{prmp}|C_{\max}$ by IP [62].

Pei et al. [73] are the first authors to consider the optimization of the two objectives $C_{\max}$ and TEC separately in an unrelated parallel machines setting. Although they actually formulated the problem as a mixed-integer quadratic program that requires the optimization of a linear combination of $C_{\max}$ and TEC, the authors first reformulated the model by exploiting several lemmas, and then they described a set of ad-hoc cutting planes. The authors also described an approximate algorithm based on such mathematical programming ideas, that achieved an average 4% gap with respect of the optimal solutions on the considered test benchmark. Ding et al. [35] only considered the optimization of the TEC on unrelated parallel machines, by studying $Rm||TEC$. The authors showed the NP-hardness of the problem and proposed a MILP formulation as well as a Dantzig–Wolfe decomposition based reformulation of the problem along with a column generation heuristic. Cheng et al. [27] improved the MILP formulation proposed by Ding et al. [35] by using less decision variables, while Saberi-Aliabad et al. [80] further improved the formulation by introducing several strengthening inequalities. Che et al. [19] instead considered the version of the problem characterized by continuous start times, i.e., $Rm|s_j \in \mathbb{R}_{0+}|TEC$. They proposed a basic MILP model, a possible improvement, and a two-stage heuristic. Finally, at the best of our knowledge, Tan et al. [88] are the only authors to deal with non-identical parallel machines in TOU scheduling, by proposing a MILP formulation and a GA for $Qm|\text{batch}(b)|TEC$.

Wang et al. [96] considered $Pm||C_{\max}, TEC$, that is one of the foundational problems in multi-objective parallel identical machines TOU scheduling, and provided a heuristic and a MILP formulation. In more detail, the heuristic is based on the ϵ-constraint paradigm. It computes a set of non-dominated solutions by iterating over the $O(C_{\max})$ upper bounds for the makespan and, at each iteration, building a heuristic solution that minimizes the TEC and satisfies the upper bound on the makespan. The solving steps at each iteration are constituted by two distinct components: a constructive heuristic and a local search. The constructive heuristic computes a schedule by considering the jobs with the Longest Processing Time (LPT) rule order, and then assigning each job to the set of adjacent slots with smallest cost. The local search improves the solution computed by the constructive heuristic, by shifting blocks of assigned slots on each machine. Anghinolfi et al. [11] built upon this work by providing an improved MILP formulation for the problem as well as a bi-objective heuristic. Each non-dominated point is computed by means of an enhanced constructive heuristic called Split-greedy Heuristic, and then improved with a novel local search algorithm called Exchange Search. Split-greedy Heuristic considers the jobs according to the LPT rule order, and assigns jobs by temporarily allowing the construction of a preemptive schedule that can be converted into a non-preemptive one with the same makespan and TEC. Exchange Search instead improves the TEC of a schedule by considering neighborhoods of subsets of jobs assigned to subsequent time slots. Zhou et al. [114] expanded the problem considered by Wang et al. and Anghinolfi et al. to a batch scheduling setting with release times. Formally, Zhou et al. studied $Pm|\text{batch}(b), r_j|C_{\max}, TEC$, and they proposed a multi-objective discrete differential evolution algorithm. Qian et al. [77] disregarded release times by tackling the problem $Pm|\text{batch}(b)|C_{\max}, TEC$. The authors developed a multi-objective evolution algorithm that fully exploits a clustering method able to extract information on the solutions distribution in the search space. With respect to Qian et al., Rocholl et al. [78] considered the minimization of the total weighted tardiness in place of the makespan. Rocholl et al. proposed a MILP formulation and heuristic approaches for the general case as well as several observation leading to a more compact formulation of a special version of the problem.

Luo et al. [67] are among the first authors to consider a flexible flow shop TOU scheduling problems. In more detail, Luo et al. studied a problem requiring the minimization of the TEC in such a setting, i.e., $FFc||TEC$, and proposed an ACO-based multi-objective metaheuristics. Zhang et al. [104] extended Luo et al.'s work by considering different machine speeds, and they proposed a MILP formulation for the problem as well as a modified "biogeography-based" algorithm combined with *Variable Neighborhood Search* (VNS). Zhang et al. [109] instead extended Luo et al. by introducing the "on/off" switching mechanism, and considering the minimization of the makespan and the TEC. Wang et al. [95] explored the line opened by Zhang et al. [109] by proposing a two-machine flexible flow shop where the two stages are constituted by a set of parallel identical machines followed by a batch machine. Similarly to Zhang et al., Wang et al. consider the "on/off" switching mechanism as well as the two objectives makespan and TEC. Zhang et al. also considered $FF2(Qm, Rm')||TEC, m > m'$, a two-machine flexible flow shop where the first and the second stage consist of m uniform machines and m' unrelated machines, respectively, and the number of machines in the first stage is always greater than the one in the second stage, i.e., $m > m'$ [106]. Finally, Ding et al. [34] expanded Luo et al.'s work as well, by considering a flexible flow shop with only uniform machines. The jobs are however characterized by due dates, and the two conflicting objectives are the minimization of the total tardiness and the TEC.

Conceptually, Cheng et al. [29] started a new research branch from Luo et al. [67]'s work, by simply considering a permutation flow shop problem with delay time, and requiring the minimization of the TEC. Following this track, Wang et al. [97] studied a two-machines permutation flow shop scheduling problem with the usual objective of minimizing the TEC. The authors proposed a MILP formulation as well as a heuristic based on Johnson's rule and dynamic programming. Wang et al. also provided a polynomial-time algorithm when the job sequence is fixed. Ho et al. [50] further extended Wang et al.'s work by proposing a novel formulation and heuristic for the problem. Aghelinejad et al. instead performed a mathematical modeling effort for the two-machines flow shop scheduling problem with the "on/off" switching mechanism [4, 10]. With respect to Cheng et al., Badri et al. [13] disregarded the permutation component of the flow shop, but they added the minimization of the sum of the total earliness and tardiness as a further objective. Badri et al. tackled the problem by means of a single-objective linear programming model resulting from the preliminar application of a fuzzy multi-objective approach. Instead, Peng et al. [74] tackled $Fm||TEC$ with a MILP formulation and a GA.

Finally, we deal with the few job shop scheduling studies. Among these, Kurniawan et al. [61] consider a bi-objective job shop scheduling problem requiring to minimize the TEC and the total weighted tardiness. The authors decompose the problem into the subproblems of sequencing the different operations on the machines, and determining their start time. They propose a "distributed-elite" local search based upon a genetic algorithm that encodes the operations sequence and their start time into two different gene representations. Li et al. [64] instead study a batch scheduling setting with the minimization of the makespan and TEC. In their work, they present a mathematical formulation along with some experimental results. Lastly, Jiang and Wang [53] consider a flexible job shop with the minimization of the makespan and TEC, and present both a MILP model and a hybrid *Multi-objective Evolutionary Algorithm based on Decomposition* (MOEA/D). Such a metaheuristic employs specific operators to generate new solutions by exploiting information in their neighborhoods, and it also embeds two different intensification operators.

Table 4 reports a compendium of the problems without an exact solution algorithm, according to the machine environment and the number of the objective functions.

4. Non-standard and application cases

In this section, we consider TOU scheduling problems that do not fit the above classification due to particular optimization objectives, structural features of the manufacturing system, or scope in their own industrial setting.

4.1. Problems with non-standard objective functions

In this subsection, we focus on the problems that require the minimization of an unusual or particular objective function. As a first example, Penn and Raviv [75] considered a single-machine problem that requires the maximization of a profit measure associated with a non-preemptive schedule of a subset of the given jobs, each characterized by a non-negative profit. The profit of a schedule is the difference between the total revenue of the scheduled jobs and the TEC. While the general case for such a problem is NP-hard, the authors present a pseudo-polynomial time algorithm for the preemptive version of the problem. Zeng et al. [101] studied a uniform parallel machines environment where the total number of machines has to be minimized along with the TEC. The authors provided a MILP model, and developed an ILS framework by building upon the greedy insertion heuristic proposed by Che et al. [18]. Gong et al. [44] instead proposed a flexible job scheduling problem with job recirculation and operation sequence-dependent setups. Alongside the makespan and the TEC, the authors take into account three other different objectives that may arise in a practical manufacturing setting: the total labor cost, the maximal workload, and the total workload. Batista Abikarram et al. [14] expanded the model of Shrouf et al. [82] by taking into account demand charges as additional energy consumption in a parallel machines environment. Tan et al. [86] instead aggregated energy consumption with additional costs due to production load shifting (such as employee overtime costs and gas emissions penalties) in a complex batch scheduling setting. Finally, Chen et al. [22] and Zhang et al. [107] also addressed environmental concerns by integrating pollutant emissions within the optimization objectives, respectively. Lee et al. [63] instead considered the minimization of the sum of the TEC and the just-in-time (JIT) cost of a schedule for a single-machine problem. The JIT cost is given as the sum of the mean squared earliness and the tardiness of the jobs, a relevant performance measures used in manufacturing

Class	Problem	Article	Solution Approach
Single-objective single-machine scheduling	$1\vert\text{prmp}, w_j\vert \sum_{j\in\mathcal{J}} w_j C_j + TEC$	Chen et al. [21]	PTAS
	$1\vert\text{prmp}, r_j, w_j\vert \sum_{j\in\mathcal{J}} w_j(C_j - r_j) + TEC$	Kulkarni and Munagala [56]	PTAS
	$1\vert\vert TEC$	Chen and Zhang [20]	FPTAS (π has at most 2 valleys)
	$1\vert q_j, s_j \in \mathbb{R}_{0+}\vert TEC$	Che et al. [18]	MILP formulation, Greedy insertion heuristic
	$1\vert q_j, s_j \in \mathbb{R}_{0+}\vert TEC$	Zhang et al. [105]	Greedy insertion heuristic algorithm
	$1\vert\text{speed}, q_j, s_j \in \mathbb{R}_{0+}, w_j\vert TEC$	Fang et al. [38]	$\sum_{k=1}^{K}(c_k\ /\ \min_{t\in\mathcal{T}} c_t)^{\delta//(\delta-1)}$-approximation algorithm, $\delta > 0$, when $p_j = w_j/v$ and $q_j = v^\delta$, being v the processing speed
	$1\vert\text{on/off}\vert TEC$	Shrouf et al. [82]	MILP, GA
	$1\vert\text{on/off}\vert TEC$	Aghelinejad et al. [5]	MILP
	$1\vert\text{on/off}\vert TEC$	Aghelinejad et al. [8]	MILP, Heuristic, GA
	$1\vert\text{on/off}\vert TEC$	Aghelinejad et al. [3]	New lower bounds for MILP formulation
	$1\vert\text{batch}(b)\vert TEC$	Cheng et al. [25]	MILP
Multi-objective single-machine scheduling	$1\vert\text{prmp}\vert C_{\max}, TEC$	Rubaiee and Yildirim [79]	MILP, ACO-based algorithms
	$1\vert\vert \sum_{j\in\mathcal{J}} w_j T_j, TEC$	Kurniawan et al. [60]	MILP, Hybrid GA with random insertion
	$1\vert\text{batch}(b)\vert C_{\max}, TEC$	Cheng et al. [26]	MILP
		Cheng et al. [23]	MILP, exact ϵ-constraint algorithm
		Cheng et al. [24]	Heuristic-based ϵ-constraint heuristics
		Zhang et al. [110]	MILP, Heuristics
		Wu et al. [98]	MILP, Heuristics
	$1\vert\text{batch}(b), r_j\vert C_{\max}, TEC$	Zhou et al. [113]	MILP, Hybrid multi-objective meta-heuristic algorithm
Multi-objective parallel identical machines	$Pm\vert\vert C_{\max}, TEC$	Wang et al. [96]	MILP, Heuristic, GA
		Anghinolfi et al. [11]	MILP, "Split-greedy" heuristic, "Exchange Search" local search
	$Pm\vert\text{batch}(b), r_j\vert C_{\max}, TEC$	Zhou et al. [114]	MILP, Multi-objective differential EA
	$Pm\vert\text{batch}(b)\vert C_{\max}, TEC$	Qian et al. [77]	MILP, Multi-objective EA based on adaptive clustering
	$Pm\vert\text{batch}(b)\vert \sum_{j\in\mathcal{J}} w_j T_j, TEC$	Rocholl et al. [78]	MILP, NSGA-II with embedded heuristics
Uniform parallel machines	$Qm\vert\text{batch}(b)\vert TEC$	Tan et al. [88]	MILP, SPGA, MPGA
Single-objective unrelated parallel machines	$Rm\vert s_j \in \mathbb{R}_{0+}\vert TEC$	Ding et al. [35]	MILP
		Che et al. [19]	MILP, Two-stage heuristic
		Cheng et al. [27]	MILP
		Saberi-Aliabad et al. [80]	MILP
	$Rm\vert\vert KC_{\max} + TEC,\ K > 0$	Moon et al. [69]	MILP, Hybrid GA
		Cheng et al. [28]	MILP
		Kurniawan et al. [57]	"Triple-chromosome" GA
	$Rm\vert s_j \in \mathbb{R}_{0+}\vert KC_{\max} + TEC,\ K > 0$	Kurniawan et al. [59]	MILP, GA
	$Rm\vert\text{prmp}, s_j \in \mathbb{R}_{0+}\vert C_{\max} + TEC$	Chen et al. [21]	$O(K^2)$ + time for solving $Rm\vert\text{prmp}\vert C_{\max}$ by IP [62]
Multi-objective unrelated parallel machines	$Rm\vert\vert C_{\max}, TEC$	Pei et al. [73]	MILP, Approximate algorithm
Single-objective flow shops	$F2\vert\text{prmu}\vert TEC$	Wang et al. [97]	MILP, ILS
		Ho et al. [50]	Heuristics
	$F2\vert\text{on/off}\vert TEC$	Aghelinejad et al. [4]	Two MIP formulations
		Aghelinejad et al. [10]	LP formulation
	$Fm\vert\vert TEC$	Peng et al. [74]	ILP, PSO
	$Fm\vert\text{prmu}\vert TEC$	Cheng et al. [29]	MILP, GA
	$FF2(Qm, Rm')\vert\vert TEC, m > m'$	Zhang et al. [106]	MILP, TS - Greedy insertion algorithm
	$FFc\vert\vert TEC$	Luo et al. [67]	ACO-based metaheuristic
	$FFc\vert\text{speed}\vert KC_{\max} + TEC$	Zhang et al. [104]	MILP formulation, Modified "biogeography-based" algorithm combined with VNS
Multi-objective flow shops	$Fm\vert\vert TEC, \sum_{j\in\mathcal{J}} E_j + T_j$	Badri et al. [13]	Single-objective LP after multi-objective fuzzy programming
	$Fm\vert\text{prmu}, w_j\vert \sum_{j\in\mathcal{J}} w_j T_j, TEC$	Kurniawan and Fujimura [58]	SPEA2-based metaheuristic
	$Fm\vert\text{prmu}\vert C_{\max}, TEC$	Wang et al. [91]	MILP
	$FF2(Pm, \text{batch}(b))\vert\text{on/off}\vert C_{\max}, TEC$	Wang et al. [95]	MILP, Constructive heuristic with local search, TS, ACO
	$FFc\vert\text{on/off}\vert C_{\max}, TEC$	Zhang et al. [109]	SPEA2
	$FFc(Qm)\vert d_j\vert \sum_{j\in\mathcal{J}} T_j, TEC$	Ding et al. [34]	MILP, Hybrid PSO
Multi-objective job shops	$Jm\vert\vert \sum_{j\in\mathcal{J}} w_j T_j, TEC$	Kurniawan et al. [61]	Distributed-elite LS based on GA
	$Jm\vert\text{batch}(b)\vert C_{\max}, TEC$	Li et al. [64]	MILP
	$FJc\vert\vert C_{\max}, TEC$	Jiang and Wang [53]	MILP, Hybrid MOEA/D

Table 4
Integer programming algorithms, approximation algorithms, heuristics and metaheuristics for different JSTP problem versions.

productions that require a certain degree of timeliness. The authors experimentally tested their dynamic control method on a real case involving a milling process performed by a HAAS machine. Gong et al. [43] considered manufacturing unit processes by studying the problem of minimizing the TEC of the schedule of a set of jobs with due dates on a single machine. More specifically, the authors used finite state machines to describe the energetic transitions of the machines, and they also implemented a genetic algorithm for the problem. Finally, they validated their approach on a real case study based on the measurements of a griding machines and the energy prices.

4.2. Technological features

Researchers also focused on modeling particular functions of the manufacturing chain. For instance, Geng et al. [41] proposed a problem based on a type of flexible-flow shop called "re-entrant" [46], and tackle it with an improved multi-objective "ant lion" optimization algorithm. Differently from Geng et al. [41], Wang [93] considered a single-machine setting with a particular technological feature, which is the calibration phase, required to process jobs. Specifically, if the calibration starts at time t, then the machine can process any job in the time slots $t, t+1, \ldots, t+X$

for some fixed $X \in \mathbb{N}$. The objective is to minimize the TEC, while calibrating the machine at most a fixed amount of times. Kong et al. [54] instead considered the dynamic disruptions that can affect manufacturing systems. The authors modeled such inconveniences as "arrival" jobs, and they formulated a rescheduling problem that requires to schedule such jobs alongside a set of the "original" jobs intended for processing in order to minimize the TEC. Tan and Cui [89] again considered the minimization of the TEC, but they introduced a constraint on the maximum power at the peak usage.

4.3. Project scheduling

Several research efforts successfully integrated the TOU framework within project scheduling [15] problems. As an example, Najafzad et al. [70] studied a bi-objective multi-skill project scheduling problem that consists in scheduling activities in order to minimize the total completion time and project cost. The project manager has to perform a trade-off between low-energy processing in off-peak hours and the resulting increase in wages due to shift differentials. Similarly to Najafzad et al., Javanmard et al. [52] considered a project scheduling problem with a multi-skill workforce, with the aim of the reducing the TEC while respecting the projects priorities as much as possible. Maghsoudlou et al. [68] presented again a multi-skilled project scheduling problem under TOU pricing with the objective of generating a preemptive schedule to minimize the TEC. Wu et al. [99] instead aimed at optimizing the consumption of the multiple resources involved in production. Du et al. [36] proposed a bi-objective model for a resource-constrained (project scheduling) problem with activity splitting and recombining, to optimize the project delay and TEC.

4.4. Handling machines maintenance

Some authors studied production problems by examining the details and the problems of manufacturing sites: from the strategic planning of multiple cooperative sites to the handling of production inconveniences. Many authors indeed considered preventive [12, 84] or planned [31, 32] maintenance in production. In fact, machines availability constitutes a serious issue in long-term production processes. A careful scheduling plan decreases the average unavailability time of a machine, thus lessening the causes of disruption in production. Sin and Chung [84] enhanced the study of Shrouf et al. [82] by considering the optimization of the TEC on a single machine with the "on/off" mechanism by adding preventive maintenance. The authors assumed a specific closed-form expression for the probability distribution of having the machine functioning at any given time. Assia et al. [12] provided a model for the problem consisting of minimizing the TEC of a schedule on unrelated parallel machines with stochastic preventive maintenance, by building upon the work of Ding et al. [35]. Cui et al. instead considered maintenance planning on a single machine [32], and later studied it as a part of a flow shop [31].

4.5. Inteoperation of multiple facilities

Zhang et al. [108] examined the inter-operation of multiple factories in an electrical grid under TOU-based tariffs. Specifically, such a grid consists of commercial and residential buildings as well as manufacturing facilities. Zhang et al. modeled the demand of commercial and residential buildings by taking into account air conditioning, heating, lightning, ventilation, and water heaters. In this setting, the authors formulate a flow shop scheduling problem where manufacturing facilities can exchange information with each other, to reduce the energy consumption while satisfying all the electricity demands in the grid. Sharma et al. [81] provided an "econological" model of a manufacturing enterprise constituted by multiple speed-scaling machines by integrating both economic and ecological objectives. In more detail, Sharma et al. proposed a flow shop scheduling problem that considers speed-scaling as a means to reduce energy consumption in specific time frames as well as the electrical load power of each machine and a measure of carbon footprint.

4.6. Applications to metallurgy

The literature also offers several efforts towards the efficient exploitation of TOU pricing schemes as a means of cutting expenses in industry production. Hadera et al. [48] and Zeng and Sun [102] are among the first authors to integrate TOU prices in iron and steel production scheduling. While the former authors focused on the melt shop section of a stainless steel plant, the latter specifically considered steam power systems such as boilers and steam turbines, while taking into account surplus byproduct gas flows. Zhao et al. [112] specifically addressed the ecological concern of reducing the byproduct gases in steel production. Specifically, they considered the minimization of the sum of the gasholder penalty and the electricity purchasing costs. Cao et al. [16] instead described the problem of simultaneously minimizing the makespan and TEC for the production planning of an iron-steel plant. However, in this setting, the TEC also depends on both the self-generation electricity costs and by the on-grid electrovalence. The authors presented a mathematical model, alongside a version of the SPEA2 metaheuristic tailored for the problem. Zhao et al. [111] faced a multi-stage production problem that specifically models the rolling process of steel within an electric grid. The authors first formulated the problem as a MINLP model with generalized disjunctive programming constraints, and then they reformulated it as a MILP model. Yang et al. [100] integrated uncertainty by considering stochastic metal elements concentration in scrap steel charge within the production scheduling of a scrap steel melt shop. The proposed robust optimization approach is experimentally validated by comparison with two deterministic models and two multi-stage optimization approaches. Guirong and Qiqiang [47] also considered uncertain data in scheduling, but as a part of the steelmaking-continuous casting production, and tackled the problem with the Monte Carlo based "cascade" cross-entropy algorithm. Pan et al. [72] considered a full steelmaking-refining-continuous casting framework, where TOU-based tariffs model the different time prices for electrical load tracking scheduling, and proposed both a MINLP model and an improved SPEA2 metaheuristic for the problem. Tan et al. [87] managed to combine the Hot Rolling Batch Scheduling Problem with the job-shop scheduling problem. Wang et al. [94] faced a real-world glass manufacturing problem, that falls within single-machine batch scheduling, with two heuristics based on decomposition concepts to deal with large-scale instances. Zeng et al. [103] instead specifically optimized the production scheduling of tissue article mills, which they tackled by means of multi-objective evolutionary algorithm based on decomposition and "teaching-learning" optimization combined with VNS.

4.7. Applications to energy supply

Energy supply scheduling was another study subject that garnered attention in the last years. Liu et al. [65] considered the "Virtual Power Plant", an efficient tool for smarter energy supply in an electric grid under TOU costs with transversal demand-side resources management. Sichilalu et al. [83] also focused on the electric grid and present a model for the problem of minimizing the energy cost of photovoltaic systems connected by a grid that supply power to heat pump water heaters. Instead, Wang et al. [92] investigated the impact of TOU prices on the power system operation within a unit scheduling problem for temperature control appliances. Similarly, Heydarian-Forushani et al. [49] aimed at determining the optimal TOU prices to ensure demand-side flexibility, while also optimizing the supply-side operations for a more secure and sustainable power grid.

5. Conclusions

In this article, we reviewed the literature on energy-efficient job scheduling with TOU-based tariffs, whose theoretical and practical relevance has increased considerably in the last five years. This specific class of scheduling problems are characterized by a pricing scheme (induced by TOU-based tariffs) that drives customer demand so as to relieve peak energy generation and the consequent environmental impact. We have presented the motivation behind the worldwide strive for sustainability and classified the flourishing literature from a historical point of view, while dealing with the computational details of the involved solution approaches. Our effort focused on providing researchers and practitioners with a framework that may guide them towards the most important theoretical results on the topic as well as the most prominent practical applications in sustainable manufacturing. Beyond studying both the combinatorics and the optimization aspects of the problems discussed above, which still are in the earliest phases, we believe necessary to also investigate the limits of TOU-based tariffs in containing the environmental impact of scheduling and production, as well as possible alternatives that may prove competitive or even more effective.

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