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Energy-aware job scheduling in a multi-objective production environment – An integrated DEA-OWA model

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Abstract

Manufacturing is a major source of energy consumption and, therefore, a significant contributor to emissions and greenhouse gases. This paper is concerned with evaluating different scheduling policies in a job shop system where energy-efficient scheduling is incorporated with multiple other scheduling criteria. In the production systems being investigated, the electrical energy is offered on a time-of-use (TOU) pricing regime. The objective of minimizing TOU energy costs conflicts sharply with most other traditional objectives in production scheduling. The aim is to identify best performing scheduling rules for different scenarios based on different shop congestion levels, and devise new rules to enable an improved integration of energy cost with other scheduling criteria.
A ranking approach based on data envelopment analysis (DEA) and Ordered Weighting Average (OWA) concepts is presented. The proposed methodology exploits the preference voting system embedded under the cross-efficiency (CE) matrix to derive a collective importance scale for the aggregation process. The approach is applied to 28 dispatching rules (DRs) for scheduling jobs that arrive continuously at random points in time during the production horizon. Computational results highlight the effect of energy costs on the overall ranking of the DRs, and unveil the superiority of certain rules under multi-objective performance criteria.

Keywords: Energy-efficient scheduling; Time-of-use pricing; Dispatching rule; Multi-objective scheduling; Data envelopment analysis; Cross-efficiency

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1. Introduction

The manufacturing sector is a major source of energy consumption, accounting for about 54% of the world's total delivered energy. Consequently, as the main contributor to emissions and greenhouse gases, energy-efficiency in manufacturing becomes vital to enhance sustainability and reduce environmental impact. Approaches for better energy-efficiency in manufacturing naturally tend to focus on the use of more energy-efficient equipment and alternatives to fossil fuels, such as solar and wind energy (Arabi *et al.* 2016). Although to a lesser extent, energy-efficient scheduling can also contribute significantly to reducing emissions and achieving more sustainable operations (Biel & Glock, 2016; Liang *et al*. 2019b).

This study considers energy-efficient scheduling within a typical job shop that operates in a setting where the electrical energy it uses is offered on a time-of-use (TOU) cost schedule (Dong *et al*. 2017). The price of the electrical supply has different rates, depending on the time of day. Energy suppliers use this pricing strategy to smooth the demand. In so doing, the energy provider is better able to conduct its operations in a more environmentally friendly manner, and may reduce, for instance, the need to resort to less desirable sources of energy, such as coal, to meet peak demand. Consequently, in attempting to schedule operations based on energy cost minimization objectives, the job shop managers contribute indirectly to reductions in harmful emissions.

The job shop under consideration processes job orders that continuously arrive over the production cycle. This dynamic nature of the job arrivals, where the processing requirements on the shop's machines are known only after the job order arrives, lends to the application of dispatching rules (DRs), which are simple to apply in such cases. In using DRs, jobs that are available and waiting to be processed on a machine are prioritized according to some rule, and the top priority job is loaded next on the machine. Hence, DRs are very convenient for managing a job shop that has continuous job arrivals, because the need to reconstruct a new schedule with each new job arrival is avoided.

Furthermore, the job shop operates under multiple scheduling objectives, one of which is minimizing total electricity costs. If minimizing the electricity costs was the only objective, the scheduling problem would become less complex, and an optimal schedule would see operations restricted to the off-peak (lowest price) period. This is not a reasonable solution, because the consequential costs related to longer completion times, more work-in-process, delay in delivery to customers, etc., would by far offset any savings from the energy bill. Therefore, production scheduling under TOU electricity costs maybe regarded as an inherently multi-criteria decision problem. Much of the published research deals with this problem by viewing it as a single objective problem to minimize total energy costs, subject to additional constraints to guarantee minimum levels of throughput. In an attempt to integrate adequately energy-efficiency into the job shop, we adopt seven additional scheduling objectives alongside minimizing total cost.

The quality of the job scheduling methodology directly affects overall performance in terms of the multiple performance criteria, such as percentage of jobs completed on time, average job flowtimes, total energy consumed, etc. Reactive scheduling approaches are ideal for dynamic, non-predictive environments characterized by external uncertainties, such as arrival of new job orders. In a reactive approach, the schedule is modified in real-time with minimal disruption to existing operations, and without having to readjust any pre-planned schedules. The DRs are a quick, convenient and easily implemented form of reactive scheduling, and there exists a large variety of DRs that maybe used. However, performance of DRs is very much problem dependent, and there rarely exists a unique DR that dominates all others for a particular criterion. Moreover, a DR that performs favorably for one criterion may easily function poorly elsewhere. Thus, for multiple criteria, the dispatching problem is one of identifying the DR that best satisfies the performance criteria collectively. One way to achieve such an objective is ranking the DRs through a methodology that allows a simultaneous evaluation of the performance measures. Data envelopment analysis (DEA) is a good tool for this purpose. By treating the different performance values resulting from the application of a particular DR as system outputs, DEA may be used to identify the efficient DRs for the job shop system under consideration.

DEA is an optimization approach proven for its strength in evaluating performance of decision making units (DMUs) that employ multiple inputs to produce multiple outputs (Sow *et al*., 2016; Oukil & Al-Zidi, 2018; Soltani *et al*., 2021). Moreover, DEA has the potential to categorize DMUs as efficient or inefficient without a need for *a priori* preference settings on inputs and outputs (Oukil & Govindaluri, 2020; Al-Mezeini *et al*., 2020; Oukil *et al*., 2021).

Viewing a DR as a DMU, the earliest studies that investigated the problem of selecting DRs using DEA are due to Chang *et al*. (1996) and Braglia & Petroni (1999). However, as pointed in El-Bouri & Amin (2015), these studies used a standard DEA model with undesirable outputs, which may invalidate the results produced. El-Bouri & Amin (2015) proposed an approach that applies ordered weighting average (OWA) aggregation prior to a DEA model with only outputs to rank the DRs. However, the latter approach does not consider explicitly the desirability aspect of the outputs or the possible occurrence of more than one efficient DR. Recently, Oukil & El-Bouri (2021) addressed these issues through a DEA cross-efficiency (CE) approach (Sexton *et al.* 1986) that is grounded on an extension of the Maximum Resonated Appreciative (MRA) model (Oral *et al*., 2015).
Regardless of the approach, it is noticeable that none of the existing DEA-based studies has discussed the sustainability of the DR ranking process in production environments where minimizing energy consumption continues to be one of the key

challenges of decision makers (DMs). Accordingly, we develop an approach that integrates energy as a major performance criterion for the evaluation of a DR. Building on the CE framework of Oukil & El-Bouri (2021), the proposed procedure exploits the preference voting system embedded under the CE matrix (Angiz *et al.* 2013) to enhance the robustness of the ranking patterns. Instead of resorting to the OWA operator (Yager, 1988) for computing the aggregate scores, a collective importance scale is applied over the aggregation process to strengthen the robustness of the ranking model besides diluting potential discrepancies that may result from situations where different CE scores produce same number of votes. Here, we introduce the concept of "aggregate vote" as a substitute to aggregate score.

The proposed ranking methodology is evaluated on a 10-machine job shop production system that processes continuously arriving job orders. Operations are managed by the use of a DR, which prioritizes the queued jobs at each machine. The objective is to implement the DR which best enables a set of different performance objectives to be met to the greatest extent possible. Eight performance objectives are identified as pertinent in production scheduling. A total of 28 DRs are selected for the computational analysis. These DRs include well-known rules that are frequently employed in job shop applications, together with a set of special rules proposed here explicitly for minimizing the electricity costs under a TOU pricing plan.

The methodology proposed in this paper is intended to provide managers with a decision support tool for selecting best energy-efficient DRs to apply in job shop environments characterized by continuous arrival of job orders, along with multiple, conflicting objectives. The rankings suggested by this methodology allow decision makers to select the DRs that are the most effective in aggregately satisfying the given set of multiple criteria.

The remaining sections of this paper unfold as follows. Section 2 reviews the literature pertaining to energy-efficient scheduling. The contextual settings of the job shop production systems under consideration are explained in Section 3. The proposed ranking methodology is presented in Section 4 and computationally evaluated in Section 5. We conclude with a summary of the results besides possible research venues in section 6.

2. Literature review

Energy-efficient scheduling relates to the different methods and strategies for manipulating production schedules with the aim of reduced energy consumption. This includes startup and shutdown of machines to minimize idle machine running times (Fernandez *et al*., 2013; Shrouf *et al*., 2014; Zhang *et al*., 2017), varying machine speeds (Luo *et al*., 2013; Jiang *et al*., 2018), scheduling on machines that have different energy consumption rates (Tigane *et al*., 2019), and taking advantage of variable energy pricing.

Gahm *et al*. (2016) suggested a framework for energy-efficient scheduling (EES), which categorizes research on this topic in three dimensions: “energetic coverage”, “energy supply” and “energy demand”. The first concerns reduction of actual demand, the second refers to the characteristics of the power supply provided to the user, and the third relates to the manner the energy is applied during the production. Provision of energy according to TOU pricing falls under the second dimension, specifically, within a classification covering price-driven demand responses. The review that follows is limited to those EES approaches that are associated with TOU pricing for energy.

TOU pricing strategies are basically of two types: hourly pricing, and prices fixed for time-of-day segments, usually referred to as peak, low and mid-peak demand periods. The time-of-day pricing aims to smooth demand by encouraging a shift away from the peak periods, which usually occur during the weekday working hours. While TOU pricing is meant to encourage postponement of activities to favorably priced periods, such postponement is usually not helpful in industries whose scheduling goals are to complete batch production in minimal cycle time, and to meet delivery deadlines. Nevertheless, EES seeks solutions that enable an organization to achieve its time-based goals, while utilizing TOU pricing to gain reductions in energy costs.

A method for dealing with such dual or multiple objectives is to combine them into a single (composite) objective function, and assign costs or penalties for deviations from each of the function’s components. For example, Mitra *et al*. (2012) suggested an objective function that sums inventory holding costs with the hourly-priced energy costs arising from transitions between machine startup and shutdown states. Moon & Park (2014) employed an objective function that includes both energy costs and penalty weights to control the length of the makespan in a flowshop. Yusta *et al*. (2010) formulated a cost function that combines machining costs and the hourly costs for electricity based on the spot market. Kurniawan *et al*. (2017) investigated a similar case for a system of unrelated parallel machines.

A more commonly used approach is to simply consider a single objective for minimizing total energy cost (TEC), while constraining the scheduling problem to meet a specified amount of production level within a defined time horizon. Examples of this approach include Shrouf *et al*. (2014), who investigated minimizing TEC in a single machine shop, with different machine operating modes (processing, idle or off); Ashok (2006) implemented an integer programming model to minimize total monthly energy costs under a constraint to achieve a target level of production. Babu & Ashok (2008) investigated similar objectives in a chemical production plant that is modeled as a jobshop production system. Wang & Li (2013) considered minimization of total electricity costs while maintaining a required level of average cumulative production, with decisions of when to power down and power up the machines during the production horizon. Castro *et al*. (2011) considered a multiproduct continuous production plant, and formulated an energy cost relationship that is minimized as a single objective, subject to hard constraints on demand fulfillment and resource availability.

Other researchers used a combined approach, employing composite objective functions, along with constraints to limit the makespan or to ensure desired production levels. For example, Fernandez *et al.* (2013) proposed an objective function that incorporated inventory holding costs with electricity costs, subject to constraints for maintaining desired levels of throughput. They modeled an automotive assembly unit, where in-process buffers are managed to avoid starving machines during off-peak periods. Sun *et al.* (2014) considered the identical problem, but included production loss penalty costs in the objective function.

A substantial number of research studies have also considered the EES problem with TOU pricing from a purely multi-criteria perspective. The criteria are typically the dual objectives of makespan and energy cost minimization. Often, these bi-criteria problems are handled by finding Pareto optimal schedules. A Pareto optimal schedule is one for which no other schedule exists with lower values for the objective functions, such as simultaneously a lower energy cost and shorter makespan. Construction of a 'frontier' of such Pareto optimal solutions enables decision makers to gauge the trade-off in improving performance in one of the two criteria at the expense of the other (Ding *et al*., 2015; Cheng *et al*., 2018; He *et al*., 2014; Zhou *et al*., 2020).

Non-Pareto approaches for multi-criteria optimization are also prevalent. Luo *et al*. (2013) employed ant colony optimization for a hybrid flowshop under TOU electricity prices, and variable speed machines. Zhang *et al*. (2014) proposed an integer programming formulation for minimizing electricity costs and carbon emissions as two separate objectives in a flowshop system, without compromising production throughput. The assumption for this is that high carbon emission sources are frequently resorted to, in some regions, in order to meet peak electricity demands. Castro *et al.* (2013) considered four different objectives separately in a flowshop model of a steel plant, including minimizing the makespan and energy costs. They noted that weighted sums of the different criteria may be implemented to achieve a compromise between the gains achieved from lowered energy costs, versus the increased makespan. Masmoudi *et al*. (2017) proposed a genetic algorithm for a single-item capacitated lot-sizing problem in a flowshop.

Another tactic for managing the conflicting objectives of minimizing makespan, while minimizing energy costs, is to break the scheduling problem into two stages. In the first stage, a schedule that minimizes the makespan is generated, and that schedule is then re-arranged in the second stage so that the energy cost is minimized, subject to the makespan obtained from the first stage not being increased. In Tan *et al*. (2013), for example, the maximum completion times are determined from a mathematical programming solution, and then a minimum energy schedule is obtained from another model that preserves the completion times from the first stage.

Considering specifically job shop scheduling under TOU pricing with multiple objectives, the published literature is sparser than that available for flowshops and parallel machine systems (Jiang *et al*., 2018). EES in jobshops with multiple objectives has been investigated in Pach *et al.* (2014) and Liang *et al.* (2019a). With the exception of Pach *et al.* (2014), who considered three criteria in their objective function, the other studies considered only two. To the best of our knowledge there are no publications dealing with more than three criteria, with total energy cost being one of the criteria, in a job-shop that experiences dynamic job arrivals and is scheduled reactively by the application of DRs. Such cases for jobshops and flowshops have indeed been investigated previously (Chang *et al*., 1996; Braglia & Petroni, 1999; Amin & El-Bouri, 2018), but not with the TOU energy criterion. The present study aims to address this gap by investigating energy costs as one among several other scheduling criteria, and how the presence of this energy criterion affects the performance of traditional DRs in a multi-objective scenario.

3. Problem description

The proposed DEA methodology is applied to a 10-machine job shop production system that processes job orders which arrive at random points in time throughout the production cycle. Every job requires processing operations once on each of the ten machines, but not necessarily in the same order. The processing time requirements on each of the machines, and the order in which the machines need to be visited, become known only after the job's arrival. In addition, every job has a completion time deadline which, if exceeded, incurs a penalty proportional to the length of the delay. Operations are scheduled by applying a DR, which prioritizes the queued jobs at each machine. The objective is to implement the DR which best enables a set of different performance objectives to be met to the greatest extent possible. Eight performance objectives, deemed pertinent in production scheduling, are considered.

Let

s = index for job number.

q = index for machine number.

t = index for the TOU period.

P = total number of jobs processed.

a_s = arrival time of job s at the jobshop.
v_s = power requirements factor for job s.
c_t = cost of electricity per unit time during TOU period t.
h_{st} = duration of processing operations for job s during TOU period t.
D_s = due date for job s.
C_s = completion time of job s's final operation.
Q_q = number of jobs in queue at machine q.

Using the above notation, the eight performance measures are described as shown in Table 1.

Table 1. Performance measures for job shop scheduling

Criterion	Performance measure
Mean Flowtime	$\overline{F} = \frac{1}{P}\sum_{s=1}^{P}(C_s - a_s)$
Maximum Flowtime	$C_{\max} = \max\{C_s - a_s\}\ s = 1,\ldots,P$
Max WIP	$WIP_{\max} = \max\{\max\ Q_q\}\ q = 1,\ldots,M$
Mean Tardiness	$\overline{T} = \frac{1}{P}\sum_{s=1}^{P}(C_s - D_s)^+$
Percentage tardy	$U_T = \sum_{s=1}^{P}(C_s - D_s)^+$
Maximum Tardiness	$L_{\max} = \max\{C_s - D_s\}\ s = 1,\ldots,P$
Earliness + Tardiness	$\overline{E+T} = \sum_{s=1}^{P}\lvert C_s - D_s\rvert$
Electricity Cost	$G = \sum_{s=1}^{P}\sum_{t=1}^{3} v_s h_{st} c_t$

3.1. Dispatching rules

A total of 28 DRs are selected for the computational analysis. These DRs include well-known rules that are frequently employed in jobshop applications, together with a set of special rules proposed here explicitly for minimizing the electricity costs under a TOU pricing plan. Among the 28 selected DRs are the following: Shortest Processing Time (SPT), First-in First-out (FIFO), Earliest Due Date (EDD), Modified Due Date (MDD), Critical Ratio (CR), Least Work Remaining (LWKR), Apparent Tardiness Cost (ATC), Cost Over Time (COVERT), work-in-next-queue (WINQ), processing time plus work-in-next-queue (PT+WINQ), processing time plus work-in-next-queue plus slack time (PT+WINQ+SL), processing time plus work-in-next-queue plus critical ratio (PT+WINQ+CR). Full details for these DRs are found in Amin & El-Bouri (2018). In addition, the enhanced critical ratio (ECR) method

(Chiang & Fu, 2007), ratio of slack time to remaining operations (Slack/NO; Baker, 1974), and twice the processing time plus least work remaining (2PT+LWKR; Sels *et al*., 2012) rules are considered. Finally, a collection of nine DRs developed specifically for the electricity cost objective are proposed. These DRs are presented in Table 2, and the ones that begin with the prefix F work by first fitting as many jobs as possible, sorted according to power requirement factor (PRF) ratings, in the remaining time of the current TOU period. These jobs are then prioritized according to a select rule, as indicated in Table 2.

Table 2. Energy-oriented Dispatching Rules

Dispatching Rule	Priority Policy
Least TOU cost (LTOUC)	Sort in order of increasing value of $v_s \times c_s$ for current TOU period.
DENE	Sort in order of increasing v_s and dispatch the job occupying the median position. If the number of waiting jobs is an even number, then assume the median position is the integer component of $n/2$.
DLDM	Maximum v_s during off-peak period, Minimum v_s during peak, DENE otherwise.
SLSM	Minimum v_s if peak, Maximum v_s if off-peak, otherwise SPT.
SLSS	Minimum v_s if peak, SPT otherwise.
F - SPT	For peak period, sort based on increasing order of v_s. Find the first n' jobs from this sequence that can fit in the remaining time of the peak period, and process them according to SPT. For off-peak, repeat as above with initial sorting based on maximum v_s. Otherwise, use SPT.
F - LWKR	Same as F - SPT, but the n' jobs are processed according to LWKR instead of SPT.
F - Covert	Same as F - SPT, but the n' jobs are processed according to COVERT with $h = 0.5$ instead of SPT.
F - PXE	Same as F - SPT, but the n' jobs are processed in increasing order of $p_{sq} \times v_s$ instead of SPT.

The TOU electricity pricing plan adopted in our computational analysis is taken from a North American city, and it is similar to mainstream practices. It divides the 24-hour day into 4 periods. Two of these periods are mid-peak, occurring from 7:00 a.m. to 11:00 a.m., and again from 5:00 p.m. to 7:00 p.m. The peak period itself runs from 11:00 a.m. to 5:00 p.m., and the off-peak is from 7:00 p.m. to 7:00 a.m. the following day. The peak tariff is taken as twice the off-peak one, and the mid-peak tariff is 50% higher than the off-peak pricing. It is further assumed that production occurs only during the weekdays, and the shop runs three shifts continuously 24 hours daily, starting 7 a.m. Monday and ending Saturday 7 a.m. Furthermore, any work in progress on the machines at the end of the week is interrupted, and resumed at the start of the following work week.

3.2. Test data

The performance of the 28 DRs is evaluated by means of simulations run on a 10-machine jobshop, using random test problems. A test problem is composed of 10,000 jobs that arrive at randomly generated points in time. The job arrivals are assumed to follow a Poisson distributed process with a mean inter-arrival rate λ. A job's route through the shop is assigned at random from one of 50 predefined routes. The predefined routes are also created at random, and they differ from one test instance to the other within the same set of test problems. An arrived job will have a PRF assigned randomly, from the distribution U[0.8,1.2]. This represents the job's energy demand relative to the other jobs, and it is constant on all machines visited. The processing times required for a job's operations on each of the machines are drawn randomly from the uniform distribution U[1,99]. In addition, every arriving job is assigned a due date that is established by adding to its arrival time a value equal to the sum of its processing times on the machines, multiplied by a factor, Z, representing the tightness of the due-date.

Nine sets of 10 test problem instances in each set are generated. The problems in each set represent a combination of a selected arrival rate and a due-date tightness factor. Three arrival rates and three due-date tightness levels are considered. The three levels of arrival rate are λ=0.0195, λ=0.0185 and λ=0.0175, selected such as to approximate machine utilization levels of 0.95 (high), 0.90 (medium) and 0.85 (low), respectively. Likewise, values of Z=2, 4 and 6 are used to generate test problems that exhibit tight, moderate, and loose due-dates, respectively. A test problem generated with λ=0.0195 and Z=2, for example, represents conditions found in a fairly congested shop, compounded by pressing due-dates.

Every problem instance in each of the nine test sets described above is simulated on the 10-machine jobshop 28 times, with a different DR applied in each replication. The simulations are done by employing a specially coded C program. The averaged values across the ten instances in each set, for each of the eight performance measures listed in Table 1, are recorded for every DR.

4. Methodological framework

DEA is a non-parametric approach for evaluating DMUs' performance relative to an efficiency frontier. Conventional DEA models include CCR (Charnes, Cooper & Rhodes, 1978), and BCC (Banker, Charnes & Cooper, 1984). For more on these models' development, see, e.g., Cooper *et al.* (2002) and Emrouznejad (2014). A recent review on DEA can be found in Emrouznejad & Yang (2018).

Each DR is regarded as a DMU that produces different outputs (performance criteria) for the same set of inputs (jobs processed over the job shop). Therefore, ranking DRs can be addressed as a performance analysis problem where each DR is willing to maximize its efficiency through augmenting its output production. The DEA-based methodology that we propose deploys as illustrated in Figure 1.

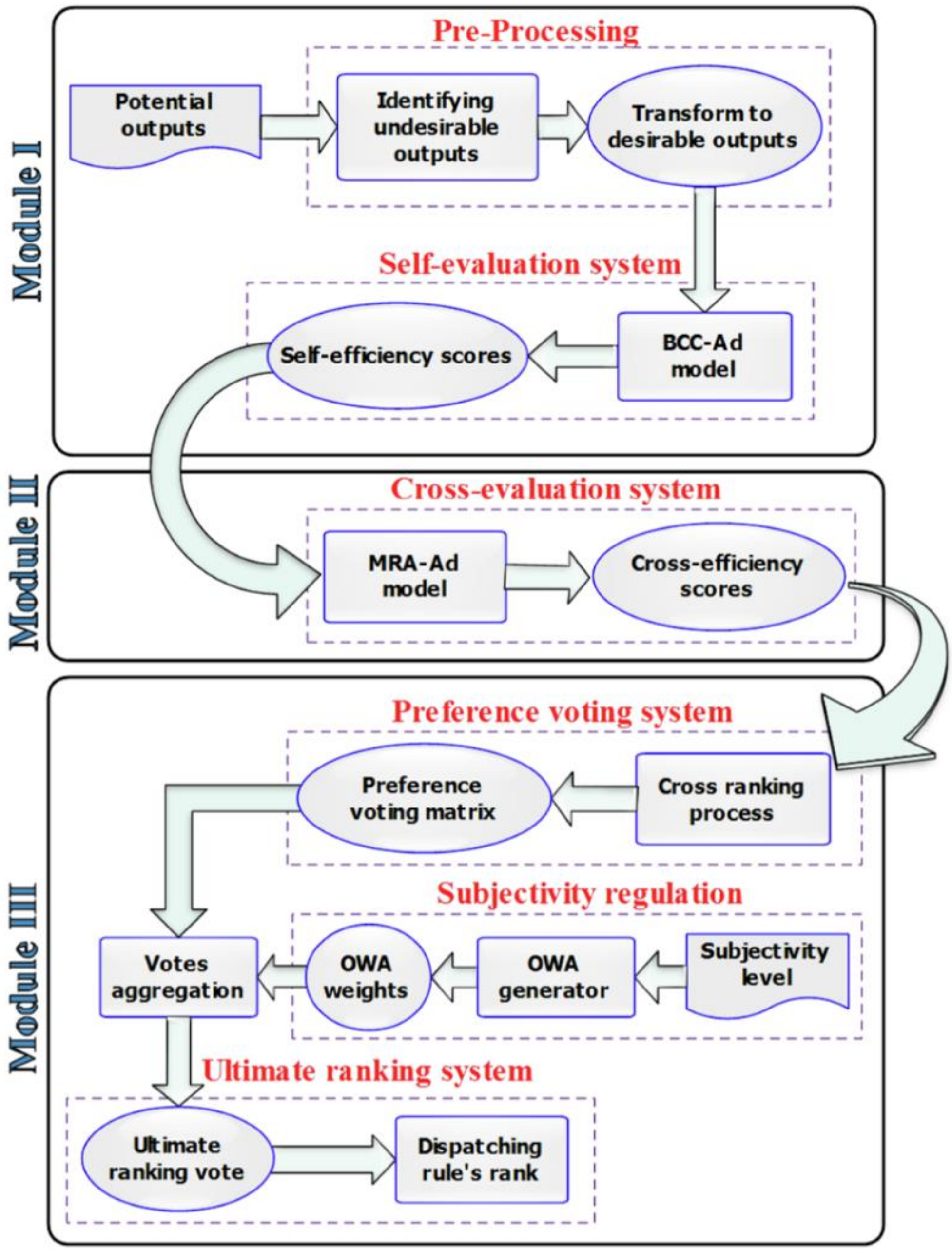

Fig. 1. Integrated DEA-OWA model for ranking dispatching rules.

4.1. *Data pre-processing*

While evaluating a DMU, the fundamental principle of standard DEA entails consuming less input to produce more output. Thus, each output complies implicitly with the preference dictum *"more is better"* (Cook *et al.*, 2014). The performance criteria adopted for the evaluation of a DR (refer Table 1) do not necessarily adhere to the latter dictum. Indeed, $C_{\max}$, $\overline{F}$, $\overline{T}$, $\overline{E+T}$, U_T, G, $WIP_{\max}$ and $L_{\max}$ need to be reduced rather than augmented, in spite of being defined as outputs. This category of outputs is known as undesirable outputs, which requires a DEA model that handles properly such a feature.

Consider a set of N DRs, where each rule r is defined with m^D desirable outputs z^D and m^U undesirable outputs z^U, with the corresponding observed values z_{jr}^D and z_{ir}^U, for $j = 1,\ldots,m^D$ and $i = 1,\ldots,m^U$. In order to incorporate desirable and undesirable outputs under the same DEA model, we apply the following linear monotone decreasing transformation (Seiford & Zhu, 2002):

$$\tilde{z}_{ir}^U = -z_{ir}^U + \partial_i + \varepsilon \qquad (1)$$

Equation (1) satisfies the translation invariance property, which preserves both linearity and convexity (Pastor & Aparicio, 2015). The multiplication of z_{ir}^U by ''-1'' enables shifting z_{ir}^U from its current status as undesirable output to its natural context where it fulfils the dictum "*the more the better*". The translation scalar ∂_i, where $\partial_i = \max_r (z_{ir}^U)$, is added to prevent negative values of $\tilde{z}_{ir}^U$. For a BCC model with a single constant input, such affine displacement of outputs does not alter the efficient frontier and, also, the classification of DMUs as inefficient or efficient is invariant to translation (Ali & Seiford, 1990). The infinitesimal scalar $\varepsilon > 0$ circumvents the occurrence of zero outputs and, hence, potential infeasibility of the DEA linear programing model.

4.2. *Adapted self-efficiency model*

Practically, all the DRs are applied simultaneously to the same job shop production systems, as described in Section 3. Consequently, we can assume that the input employed by each DR r is the same, regardless of which DR is applied. Thus, the input w_{1r} can be assigned a constant value, e.g., $w_{1r} = 1$. Under a DEA framework, output expansion becomes the only concern of each DR r willing to maximize its efficiency ψ; a stance that fits naturally the DEA output-orientation, whose BCC envelopment form, adapted to the data pre-processing context, writes as follows:

$$\text{(E-BCC)} \qquad \begin{aligned} & e_{rr}^* = \max \psi \\ & \text{s.t.} \\ & \quad \sum_{k=1}^{N} \beta_k z_{jk}^D \geq \psi\, z_{jr}^D \qquad j = 1,\ldots, m^D \qquad (2) \\ & \quad \sum_{k=1}^{N} \beta_k \tilde{z}_{ik}^U \geq \psi\, \tilde{z}_{ir}^U \qquad i = 1,\ldots, m^U \qquad (3) \\ & \quad \sum_{k=1}^{N} \beta_k w_{1k} \leq 1 \qquad (4) \\ & \quad \sum_{k=1}^{N} \beta_k = 1 \qquad (5) \\ & \quad \beta_k \geq 0 \qquad k = 1,\ldots, N \end{aligned}$$

The efficiency e^*_{rr} of DR r represents the maximal radial expansion of outputs that is required to reach the efficiency frontier for a specified level of input $w_{1r}=1$. DR r is efficient if $e^*_{rr}=1,$ otherwise it is inefficient $(e^*_{rr}>1)$. Constraints (2) to (4) indicate that reference points for DR r are linear combinations of the efficient peers. By considering a single constant input, $w_{1k}=1 \quad (k=1,\ldots,N),$ constraint (4) becomes redundant as it is dominated by the convexity constraint (5). Indeed, being an output-oriented BCC model with a single constant input, E-BCC coincides with the corresponding CCR model (Lovell and Pastor, 1999). Moreover, E-BCC turns into an output-oriented BCC model without inputs, as proven by Lovell & Pastor (1999) and Toloo & Tavana, (2017).

Model (E-BCC)'s strength resides in its ability to incorporate desirable and undesirable outputs within a unified formulation. Its multiplier form is as follows:

$$
\text{(M-BCC)} \qquad
\begin{aligned}
& e^*_{rr} = \min\ \delta_r \\
& \text{s.t.} \\
& \qquad \sum_{j=1}^{m^D} z^D_{jr}\mu_{jr} + \sum_{i=1}^{m^U} \widehat{z}^U_{ir}\widehat{\mu}_{ir} = 1 && (6) \\
& \delta_r - \sum_{j=1}^{m^D} z^D_{jk}\mu_{jr} - \sum_{i=1}^{m^U} \widehat{z}^U_{ik}\widehat{\mu}_{ir} \ge 0 \qquad k=1,\ldots,N && (7) \\
& \qquad\qquad \mu_{jr} \ge 0 \qquad\qquad j=1,\ldots,m^D \\
& \qquad\qquad\qquad \widehat{\mu}_{ir} \ge 0 \qquad i=1,\ldots,m^U
\end{aligned}
$$

The multipliers μ_{jr} and $\widehat{\mu}_{ir}$ represent, respectively, the weights selected by DR r to quantity the influence of outputs z^D_{jk} and $\widehat{z}^U_{ik}$ on its most advantageous self-evaluation (Oral *et al*., 2014). The multiplier δ_r is associated to the convexity constraint.

Although model (M-BCC) enables DRs to be categorized as efficient $(e^*_{rr}=1)$ and inefficient $(e^*_{rr}>1)$, it may fail to achieve full ranking if several efficient DRs occur. We resort to DEA cross-efficiency (CE, henceforth) to cope with this situation (Abolghasem *et al*. 2019; Navas *et al*. 2020;).

4.3. *Adapted cross-efficiency model*

Under a CE paradigm, each DR r is permitted to evaluate its peer DRs with its best own weight profile $(\boldsymbol{\mu}^*_r\ \widehat{\boldsymbol{\mu}}^*_r)$. Yet, one may find different optimal solutions $(\boldsymbol{\mu}^*_r\ \widehat{\boldsymbol{\mu}}^*_r)$. for the same objective e^*_{rr}, resulting in more than one CE score for the same CE evaluation and, hence, multiple ranking patterns (Hassan & Oukil, 2021). To palliate such a dearth, a number of alternative secondary goal models have been developed in the DEA literature, including the MRA model (Oral *et al.,* 2015). For a recent review of the alternative secondary goal models, see, e.g., Oukil (2020)

The prominence of the MRA model emanates from its potential to enable peer-evaluation of each DR with a separate set of customized weights instead of the sole and unique set of common weights $(\boldsymbol{\mu}_r^* \, \widehat{\boldsymbol{\mu}}_r^*)$. Such a desirable property allows boosting discrimination at an early stage of the ranking process through eliminating common weights, which are often a potential source of tight ranks (Oral *et al*. 2015).

The adapted form of the MRA model that combines desirable and undesirable outputs under the same output oriented formulation writes as follows.

$$
\text{(A-MRA)} \quad
\begin{array}{llll}
e_{rp}^* = \min \ \delta_p & & & \\
\quad s.t. & & & \\
 & \sum_{j=1}^{m^D} z_{jp}^D \mu_{jp} + \sum_{i=1}^{m^U} \widehat{z}_{ip}^U \widehat{\mu}_{ip} = 1 & & (8) \\
\delta_p & -\sum_{j=1}^{m^D} z_{jk}^D \mu_{jp} - \sum_{i=1}^{m^U} \widehat{z}_{ik}^U \widehat{\mu}_{ip} \geq 0 & k = 1, \ldots, N & (9) \\
\delta_p - e_{rr}^* \left(\sum_{j=1}^{m^D} z_{jp}^D \mu_{jp} - \sum_{i=1}^{m^U} \widehat{z}_{ip}^U \widehat{\mu}_{ip} \right) = 0 & & & (10) \\
 & \mu_{jp} \geq 0 & j = 1, \ldots, m^D & \\
 & \widehat{\mu}_{ip} \geq 0 & i = 1, \ldots, m^U &
\end{array}
$$

e_{rp}^* is the CE score of DR p, as assigned by the assessing DR r, using the weight profile $(\boldsymbol{\mu}_p^* \, \widehat{\boldsymbol{\mu}}_p^*)$ that sustains self-efficiency at its former level e_{rr}^*, for p=1,…,K, $p \neq r$. Model (A-MRA) is solved (K-1) times for each assessing DR r to calculate the CE scores e_{rp}^* for all DRs p for p=1,…,K and $p \neq r$. The resulting CE matrix $\boldsymbol{E}$ for $r = 1,...,K$, is:

$$
\boldsymbol{E} = \begin{bmatrix} e_{11}^* & e_{12}^* \ldots & e_{1K}^* \\ e_{21}^* & e_{22}^* \ldots & e_{2K}^* \\ \ldots & \ldots \ \ldots & \ldots \\ e_{K1}^* & e_{K2}^* \ldots & e_{KK}^* \end{bmatrix}
$$

Column $\boldsymbol{e}_p^*$ in matrix $\boldsymbol{E}$ holds the CE scores of DR p as assigned by all assessing DRs r $(r = 1, \ldots, K)$. Thus, $\boldsymbol{e}_p^*$ symbolizes the collective evaluation of DR p for $p = 1, \ldots, K$.

Usually, the ranking of the DRs requires the computation of ultimate efficiency score φ_p through some sort of aggregation technique (Oukil, 2018). The majority of CE aggregation approaches rely on the arithmetic average of column $\boldsymbol{e}_p^*$, i.e.,

$\varphi_p = \sum_{k=1}^{K} e_{kp}^{*} / K$, for each p=1,…,K, which assigns equal aggregation weights $\theta = 1/K$ to each efficiency score e_{kp}^{*}, regardless of its relative importance. In real-life, the CE scores may not be equally important with respect to either a preference scale or a priority rule suitably set for the decision making context. To allow the relative importance to be explicitly considered in CE aggregation, the OWA operator assigns dissimilar weights to the efficiency scores e_{kp}^{*} once sorted by dint of their magnitudes. This approach attaches more importance to scores with larger magnitudes (see, e.g., Wang & Chin, 2011; Oukil & Govindaluri, 2017; Amin & Oukil, 2019). Yet, the importance scale that is prompted for the DRs over each column of CE scores $\boldsymbol{e}_p^{*}$ is not stable, which affects necessarily the consistency of pertaining aggregates and, obviously, the rank patterns (Oukil, 2020). Rather than setting *a priori* the preference, it can be tacitly impelled from an agreement among the DMUs. Accordingly, we develop an aggregation procedure that exploits the preference voting system embedded under the CE matrix to set a more robust importance scale.

4.4. *Preference voting*

Practically, peer-evaluation scores can be perceived as measures of mutual appreciation of the DRs to each other (Oral *et al.,* 2014). Thus, the CEmatrix can be implicitly viewed as a voting framework where each DR holds a dual status of candidate and constituent, and deemed free to vote without outer influence (Oukil & Amin, 2015). The strength of such an approach resides in the collective consensus among DRs (Oukil, 2019) that the associated preference-voting matrix Θ aptly reflects.

$$\Theta = \begin{bmatrix} \vartheta_{11} & \vartheta_{12} \dots & \vartheta_{1K} \\ \vartheta_{21} & \vartheta_{22} \dots & \vartheta_{2K} \\ \dots & \dots \ \dots & \dots \\ \vartheta_{K1} & \vartheta_{K2} \dots & \vartheta_{KK} \end{bmatrix}$$

Each DR p is associated with a preference voting vector $\boldsymbol{\vartheta}_p = (\vartheta_{p1} \ \vartheta_{p2} \ \dots \ \vartheta_{pK})$, where ϑ_{pf} is the number of votes in support of ranking DR p at the fth position, with $K = \sum_{f=1}^{K} \vartheta_{pf}$ voters. Thus, matrix Θ encompasses the importance of each DR from a cooperative stance, entailing all DRs. As such, the importance scale that Θ reflects is much more consensual.

With the importance scale determined via Θ, the ranking of the DRs can still not be performed without *a priori* ranking scores. Instead of relying on the ultimate efficiency scores φ_p, as is the conventional practice, we introduce the ultimate ranking vote υ_p as a substitute. Accordingly, the information aggregation is restricted to the votes without recalling again the corresponding CE scores (see, e.g., Oukil, 2019).

Intuitively, the average voting score would appear as a valid metric; an option that is inevitably discarded because the total number of votes in each row p is the same i.e., $K = \sum_{f=1}^{K} \vartheta_{pf}$, leading to equal averages. However, knowing that the importance of the votes ϑ_{pf} over each row p is already established through the rank orders, the OWA operator might be an appropriate aggregation device.

4.5. *Ordered weighted averaging*

An OWA operator with a weigh vector $\gamma \in [0,1]^K$ is a function $g(\vartheta_p\,;\gamma) = \sum_{\ell=1}^{K} \gamma_\ell \vartheta_{p\ell}$ where $\vartheta_{p\ell}$ is the value of the $\ell\, th$ factor of the argument $\vartheta_p = (\vartheta_{p1}\ \vartheta_{p2}\ \ldots\ \vartheta_{pK})$ as determined by the preference-voting matrix Θ, and γ_ℓ is the associated OWA weight, with $\sum_{\ell=1}^{K} \gamma_\ell = 1.$

The OWA weight vector γ can be generated in a way that echoes the subjectivity level of the DM. Although there are several approaches for generating these weights (see, e.g., Emrouznejad & Marra, 2014), the minimax disparity models are the most frequently used approaches (Saeidi *et al.*, 2015). In our study, the following model, due to Wang & Parkan (2005), is used.

$$
\text{(WP)} \quad
\begin{array}{lll}
\min d & & \\
s.t. & & \\
\sum_{\ell=1}^{K-1} \left(\dfrac{K-\ell}{K-1} \right) \gamma_\ell = \alpha & \alpha \in [0,1] & (11) \\
\sum_{\ell=1}^{K} \gamma_\ell = 1 & & (12) \\
-d \le \gamma_\ell - \gamma_{\ell+1} \le d & \ell = 1,\ldots,K-1 & (13) \\
\gamma_\ell \ge 0 & \ell = 1,\ldots,K &
\end{array}
$$

Model (WP) aims at minimizing the deviation d between successive aggregation weights γ_ℓ and $\gamma_{\ell+1}$, $\ell = 1,\ldots,K$, as formulated by the set of constraints (13). The parameter α on the right hand side of constraint (11), represents the level of optimism of the DM, also known as orness value (Yager, 1995). The extreme values of α are $\alpha = 0$ and $\alpha = 1$, which correspond to purely pessimistic and purely optimistic DMs, respectively. A neutral attitude is quantified with $\alpha = 0.5$. Thus, orness values $0.5 < \alpha < 1$ reflect DMs that are just optimistic. Optimism being a subjective stance, the variability of α offers an opportunity to incorporate a broader range of DM's subjectivity levels over the ranking process in a regulated manner. Moreover, the robustness of resulting ranking patterns can be objectively evaluated.

Wang & Parkan (2005) showed that, if an optimistic DM desires to prevent the occurrence of a zero in the vector γ of OWA weight, α should satisfy

$$0.5 < \alpha \leq \frac{2K-1}{3(K-1)} \qquad (14)$$

As such, none of the factors in the argument $\vartheta_p = (\vartheta_{p1}\ \vartheta_{p2}\ \dots\ \vartheta_{pK})$ is excluded from the aggregation process.

4.6. *Ultimate ranking vote*

Considering the number K of DRs to be ranked, it is necessary to specify the DM's subjectivity level α, as described in Section 4.5, before solving model (WP) and generate a vector $\gamma = (\gamma_1, \dots, \gamma_{K-1}, \gamma_K)$ of OWA weights. Given a vector of votes $\vartheta_p = (\vartheta_{p1}\ \vartheta_{p2}\ \dots\ \vartheta_{pK})$ related to DR p, using vector γ as an aggregation device enables the relative importance of the votes to be realistically weighted from a collective standpoint. Thus, the ultimate ranking vote υ_p associated to DR p can be calculated as:

$$\upsilon_p = \sum_{\ell=1}^{K} \gamma_\ell \vartheta_{p\ell}. \qquad (15)$$

High values of υ_p imply necessarily that a high number of DRs voted for DR p to be in leading rank positions regardless of the magnitude of the CE score that was attached to each vote. With an aggregation process centered on the votes, the proper score-based assessment context of each DR is ignored in the ultimate ranking for more fairness.

Subsequently, sorting the elements of vector $\boldsymbol{\upsilon} = (\upsilon_1, \dots, \upsilon_K)$ from the highest to the lowest yields a possible ranking of the DRs that is likely to be sufficiently robust and fair.

5. Results and discussion

The evaluation of the new ranking procedure is carried out by treating the results from the 9 test sets described above in two separate scenarios. These scenarios are identified by the *notation 10/A/Z/ε*, where *A* is the congestion level (Low, Moderate, High), Z is the due date tightness, $Z \in \{2, 4, 6\}$, and $\varepsilon=1$ if energy cost is included as a performance measure, $\varepsilon=0$ otherwise. Further, the DM's subjectivity level is reflected with four different orness values α for each instance, hence, totalizing 72 combinations *10/A/Z/ε/α*.

The results associated to each *10/A/Z/ε/α* combination are produced via a C++ module that embeds the algorithm of the ranking procedure with all relating DEA and OWA linear programming models, beside required IBM-ILOG CPLEX libraries.

The different steps of the ranking process are deployed for instances *10/Low/Z/ε/α* prior to an ample discussion of the results produced over all *10/A/Z/ε/α* instances.

Table 3. Self-efficiency scores for instance 10/Low/Z/ε

Dispatching rule	DMU	ε=0			ε=1		
		Z=2	Z=4	Z=6	Z=2	Z=4	Z=6
ATC2	D_{01}	1.021	1.126	1.009	1.020	1.116	1.009
ATC5	D_{02}	1.015	1.116	1.000	1.015	1.110	1.000
ATC10	D_{03}	1.015	1.042	1.000	1.015	1.041	1.000
COVERT2	D_{04}	1.000	1.036	1.000	1.000	1.031	1.000
COVERT5	D_{05}	1.000	1.000	1.000	1.000	1.000	1.000
COVERT10	D_{06}	1.000	1.000	1.000	1.000	1.000	1.000
LTOUC	D_{07}	1.000	1.000	1.000	1.000	1.000	1.000
DLDM	D_{08}	1.437	1.187	1.198	1.000	1.000	1.000
ECR	D_{09}	1.000	1.000	1.000	1.000	1.000	1.000
EDD	D_{10}	1.002	1.000	1.000	1.002	1.000	1.000
F-COVERT	D_{11}	1.150	1.089	1.088	1.000	1.000	1.000
FIFO	D_{12}	1.007	1.024	1.061	1.007	1.023	1.057
DENE	D_{13}	1.428	1.168	1.178	1.000	1.000	1.000
F-SPT	D_{14}	1.152	1.089	1.086	1.000	1.000	1.000
F-pxe	D_{15}	1.154	1.116	1.111	1.000	1.000	1.000
LWKR	D_{16}	2.662	1.922	2.000	2.386	1.883	1.961
2PT+LWKR	D_{17}	1.610	1.339	1.505	1.583	1.327	1.495
F-LWK	D_{18}	1.161	1.083	1.083	1.000	1.000	1.000
MDD	D_{19}	2.988	1.745	1.002	2.685	1.702	1.002
PT+WIMQ	D_{20}	1.000	1.003	1.000	1.000	1.003	1.000
CR	D_{21}	1.119	1.107	1.090	1.119	1.105	1.088
Slack/NO	D_{22}	1.000	1.000	1.000	1.000	1.000	1.000
SLSM	D_{23}	1.156	1.089	1.088	1.000	1.000	1.000
SLSS	D_{24}	1.033	1.041	1.018	1.000	1.000	1.000
SPT	D_{25}	1.000	1.000	1.000	1.000	1.000	1.000
WINQ	D_{26}	1.000	1.065	1.059	1.000	1.062	1.054
WINQ+CR	D_{27}	1.000	1.000	1.000	1.000	1.000	1.000
WINQ+SL	D_{28}	1.050	1.079	1.011	1.050	1.070	1.011
# Efficient DMUs		10	8	12	18	16	20
Mean		1.220	1.124	1.092	1.139	1.088	1.060
STD		0.481	0.216	0.206	0.412	0.212	0.200

5.1. Preliminary evaluation of the dispatching rules

The first step of the evaluation process consists in solving model (M-BCC). The efficiency scores e^* are presented in Table 3 for *10/Low/Z/ε* instances.

These results reveal the incapacity of model (M-BCC) to achieve full ranking of the DRs, as the proportion of strongly efficient DRs ranges between 8 and 20 out of 28 DRs.

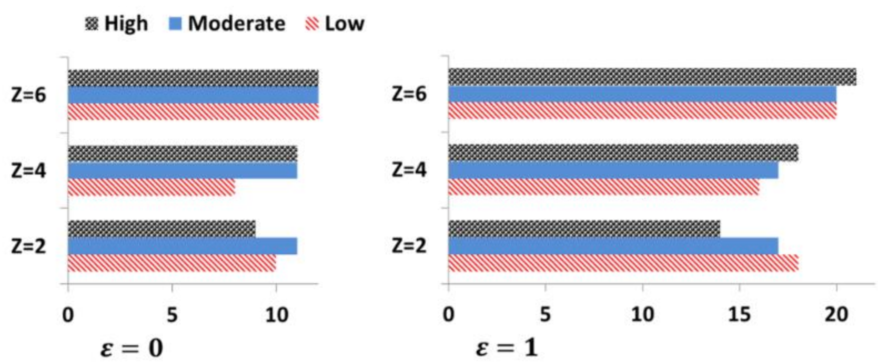

Fig. 2. Frequency of efficient dispatching rules over the job shop instances.

The frequencies shown in Figure 2 for all *10/A/Z/ε* instances stress much more such a deficiency, with a minimum of 8 efficient DRs for Z=4 under low congestion, and a maximum of 21 efficient DRs for Z=6 under high congestion. Moreover, looking at the chart of *ε*=1, it appears that these frequencies almost double when the self-efficiency DEA analysis involves energy costs. As such, self-efficiency model (M-BCC) fails to declare the best DR.
As a remedy, we implement the new ranking procedure, which is based on CE evaluation of the DRs.

5.2. Ranking dispatching rules

Model (A-MRA) is solved 27 times for each DR r defined with in instance *10/Low/Z/ε*. The CE scores e^*_{rp} $(p = 1, ..., 28; p \neq r)$ corresponding to *Z*=2 are presented in Appendix C for *ε*=0 and *ε*=1. The resulting preference-voting matrices Θ are reported in Appendix D. For instance, row DR$_2$ in Table D1 indicates that DR$_2$ is ranked first by only two DRs and its worst rank is 25*th*, allotted by only one DR.
It can be verified that the total vote in each row p is $K = 28$, for $p = 1, ..., 28$, which excludes the average voting score as an option for ranking the DRs. Meanwhile, one can exploit the existing importance scale set over the rank order of Θ and apply OWA aggregation to derive an ultimate vote υ_p.
We solve model (WP) for *K*=28 to generate a vector $\gamma = (\gamma_1, ..., \gamma_{28})$ of OWA weights for a chosen optimism level *α*. The values of *α* are chosen within the range

$(0.5,\ \alpha_{\max}]$, where $\alpha_{\max} = 0.679$ is computed for K=28 using formula (14). As a practical way to further evaluate the robustness of the ranking methodology, we widen the application scope by using different values of $\alpha \in \{0.55, 0.60, 0.65, 0.67\}$. We consider that a gap of 0.05 between the chosen values of α may be enough to cover most of the range of optimistic values $(0.5,\ 0.679]$. Such a choice of α guarantees that all the elements of the vector $\boldsymbol{\gamma} = (\gamma_1, \dots, \gamma_{28})$ are strictly positive and, hence, none of the voting scores will be excluded from the aggregation process.

The OWA weights produced are displayed in Appendix E.

The ultimate ranking votes υ_p, computed by using formula (15), are exhibited in Tables 4 and 5.

Table 4. Ultimate ranking votes for different *10/Low/Z/0/α* combinations

	Z=2				Z=4				Z=6			
DMU	**α=0.55**	**α=0.60**	**α=0.65**	**α=0.67**	**α=0.55**	**α=0.60**	**α=0.65**	**α=0.67**	**α=0.55**	**α=0.60**	**α=0.65**	**α=0.67**
D01	0.994	0.988	0.982	0.980	0.942	0.883	0.825	0.802	0.995	0.990	0.984	0.982
D02	1.016	1.033	1.049	1.055	0.927	0.854	0.781	0.751	0.987	0.975	0.962	0.957
D03	0.973	0.947	0.920	0.910	0.982	0.965	0.947	0.940	1.128	1.256	1.383	1.435
D04	1.120	1.241	1.361	1.410	0.879	0.758	0.636	0.588	0.947	0.894	0.840	0.819
D05	1.041	1.083	1.124	1.141	1.146	1.293	1.439	1.497	1.081	1.161	1.242	1.274
D06	1.228	1.457	1.685	1.776	1.249	1.498	1.747	1.847	1.259	1.519	1.778	1.882
D07	1.024	1.047	1.071	1.080	1.012	1.024	1.035	1.040	0.946	0.892	0.838	0.817
D08	0.869	0.738	0.608	0.555	0.984	0.969	0.953	0.947	0.937	0.874	0.812	0.786
D09	1.141	1.282	1.423	1.480	1.019	1.038	1.058	1.065	1.155	1.310	1.466	1.528
D10	0.845	0.690	0.534	0.472	0.919	0.839	0.758	0.726	0.908	0.817	0.725	0.688
D11	1.046	1.092	1.137	1.156	1.101	1.202	1.304	1.344	1.026	1.052	1.078	1.088
D12	0.836	0.672	0.508	0.442	0.895	0.790	0.685	0.643	0.868	0.737	0.605	0.553
D13	0.895	0.790	0.685	0.643	1.033	1.065	1.098	1.111	0.958	0.916	0.874	0.857
D14	1.032	1.064	1.095	1.108	1.105	1.210	1.315	1.357	1.021	1.041	1.062	1.070
D15	1.021	1.041	1.062	1.070	1.076	1.152	1.228	1.259	0.977	0.954	0.931	0.922
D16	0.783	0.567	0.350	0.264	0.789	0.579	0.368	0.284	0.772	0.545	0.317	0.226
D17	0.829	0.657	0.486	0.417	0.852	0.704	0.557	0.498	0.853	0.706	0.559	0.500
D18	0.974	0.948	0.922	0.912	1.124	1.248	1.372	1.422	1.065	1.130	1.195	1.221
D19	0.764	0.527	0.291	0.196	0.847	0.694	0.541	0.480	0.855	0.710	0.566	0.508
D20	1.073	1.146	1.219	1.249	0.900	0.799	0.699	0.658	1.090	1.180	1.270	1.307
D21	0.996	0.993	0.989	0.987	1.078	1.155	1.233	1.264	1.006	1.012	1.018	1.020
D22	1.227	1.454	1.681	1.771	1.123	1.247	1.370	1.420	1.104	1.208	1.313	1.354
D23	1.013	1.027	1.040	1.045	1.101	1.202	1.304	1.344	1.026	1.052	1.078	1.088
D24	1.044	1.089	1.133	1.151	1.013	1.025	1.038	1.043	0.986	0.972	0.958	0.952
D25	1.197	1.395	1.592	1.671	1.109	1.217	1.326	1.369	1.173	1.346	1.519	1.588
D26	1.259	1.519	1.778	1.882	1.016	1.031	1.047	1.053	0.987	0.975	0.962	0.957
D27	1.143	1.285	1.428	1.485	1.146	1.291	1.437	1.495	1.192	1.384	1.576	1.653
D28	0.942	0.883	0.825	0.802	0.965	0.931	0.896	0.882	0.981	0.962	0.942	0.935

Table 5. Ultimate ranking votes for different *10/Low/Z/1/α* combinations

	Z=2				Z=4				Z=6			
DMU	α=0.55	α=0.60	α=0.65	α=0.67	α=0.55	α=0.60	α=0.65	α=0.67	α=0.55	α=0.60	α=0.65	α=0.67
D_{01}	0.963	0.926	0.889	0.874	0.904	0.808	0.712	0.673	0.925	0.851	0.776	0.746
D_{02}	0.963	0.926	0.889	0.874	0.934	0.868	0.803	0.776	1.008	1.016	1.024	1.028
D_{03}	0.938	0.876	0.814	0.789	0.955	0.910	0.865	0.847	1.188	1.377	1.565	1.641
D_{04}	1.106	1.213	1.319	1.362	0.938	0.876	0.814	0.789	0.961	0.922	0.883	0.867
D_{05}	1.032	1.064	1.095	1.108	1.215	1.430	1.645	1.731	1.141	1.282	1.423	1.480
D_{06}	1.142	1.284	1.426	1.482	1.217	1.434	1.652	1.739	1.253	1.507	1.760	1.862
D_{07}	0.999	0.999	0.998	0.997	0.956	0.913	0.869	0.852	0.899	0.798	0.696	0.656
D_{08}	1.083	1.166	1.248	1.281	1.139	1.278	1.417	1.472	1.141	1.282	1.423	1.480
D_{09}	1.179	1.358	1.536	1.608	1.007	1.013	1.020	1.023	1.160	1.321	1.481	1.545
D_{10}	0.816	0.632	0.448	0.374	0.927	0.854	0.781	0.751	0.921	0.842	0.763	0.731
D_{11}	1.114	1.228	1.341	1.387	1.189	1.378	1.567	1.643	1.180	1.359	1.539	1.610
D_{12}	0.829	0.657	0.486	0.417	0.888	0.775	0.663	0.618	0.855	0.710	0.566	0.508
D_{13}	1.039	1.078	1.117	1.133	1.112	1.223	1.335	1.379	1.041	1.083	1.124	1.141
D_{14}	1.016	1.031	1.047	1.053	1.047	1.095	1.142	1.161	1.089	1.179	1.268	1.304
D_{15}	1.030	1.059	1.089	1.100	1.148	1.296	1.443	1.502	1.165	1.330	1.494	1.560
D_{16}	0.782	0.564	0.346	0.259	0.772	0.545	0.317	0.226	0.764	0.529	0.293	0.199
D_{17}	0.827	0.654	0.481	0.412	0.837	0.675	0.512	0.447	0.812	0.623	0.435	0.359
D_{18}	1.036	1.072	1.109	1.123	1.151	1.301	1.452	1.513	1.133	1.266	1.399	1.452
D_{19}	0.761	0.521	0.282	0.186	0.802	0.604	0.406	0.327	0.828	0.656	0.483	0.415
D_{20}	1.149	1.297	1.446	1.505	0.857	0.715	0.572	0.515	1.016	1.033	1.049	1.055
D_{21}	0.934	0.868	0.803	0.776	0.937	0.874	0.812	0.786	0.902	0.803	0.705	0.666
D_{22}	1.194	1.387	1.581	1.658	1.183	1.365	1.548	1.621	1.095	1.189	1.284	1.322
D_{23}	1.072	1.143	1.215	1.244	1.189	1.378	1.567	1.643	1.180	1.359	1.539	1.610
D_{24}	1.235	1.470	1.705	1.799	1.196	1.392	1.587	1.666	1.161	1.322	1.483	1.548
D_{25}	1.139	1.278	1.417	1.472	1.031	1.062	1.093	1.106	1.050	1.099	1.149	1.168
D_{26}	1.250	1.500	1.749	1.849	0.962	0.925	0.887	0.872	0.920	0.840	0.761	0.729
D_{27}	1.145	1.290	1.434	1.492	1.098	1.195	1.293	1.332	1.076	1.152	1.228	1.259
D_{28}	0.908	0.817	0.725	0.688	0.955	0.910	0.865	0.847	0.917	0.834	0.752	0.719

Subsequently, the corresponding ranking patterns are given in Tables 6 and 7.

Table 6. Ranking patterns for different *10/Low/Z/0/α* combinations

	Z=2				**Z=4**				**Z=6**			
DMU	**α=0.55**	**α=0.60**	**α=0.65**	**α=0.67**	**α=0.55**	**α=0.60**	**α=0.65**	**α=0.67**	**α=0.55**	**α=0.60**	**α=0.65**	**α=0.67**
D_{01}	18	18	18	18	20	20	20	20	14	14	14	14
D_{02}	15	15	15	15	21	21	21	21	**16**	**15**	**16**	**16**
D_{03}	20	20	20	20	18	18	18	18	**5**	**5**	**5**	**5**
D_{04}	**7**	**7**	**7**	**7**	25	25	25	25	**21**	**21**	**21**	**21**
D_{05}	**11**	**11**	**11**	**11**	**2**	**2**	**2**	**2**	**8**	**8**	**8**	**8**
D_{06}	**2**	**2**	**2**	**2**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
D_{07}	**13**	**13**	**13**	**13**	**16**	**16**	**16**	**16**	**22**	**22**	**22**	**22**
D_{08}	23	23	23	23	17	17	17	17	23	23	23	23
D_{09}	**6**	**6**	**6**	**6**	**13**	**13**	**13**	**13**	**4**	**4**	**4**	**4**
D_{10}	24	24	24	24	**22**	**22**	**22**	**22**	**24**	**24**	**24**	**24**
D_{11}	9	9	9	9	8	8	8	8	10	10	10	10
D_{12}	25	25	25	25	24	24	24	24	25	25	25	25
D_{13}	22	22	22	22	12	12	12	12	20	20	20	20
D_{14}	12	12	12	12	7	7	7	7	12	12	12	12
D_{15}	14	14	14	14	11	11	11	11	19	19	19	19
D_{16}	27	27	27	27	28	28	28	28	28	28	28	28
D_{17}	26	26	26	26	26	26	26	26	27	27	27	27
D_{18}	19	19	19	19	4	4	4	4	9	9	9	9
D_{19}	28	28	28	28	27	27	27	27	26	26	26	26
D_{20}	**8**	**8**	**8**	**8**	23	23	23	23	**7**	**7**	**7**	**7**
D_{21}	17	17	17	17	10	10	10	10	13	13	13	13
D_{22}	**3**	**3**	**3**	**3**	**5**	**5**	**5**	**5**	**6**	**6**	**6**	**6**
D_{23}	16	16	16	16	8	8	8	8	10	10	10	10
D_{24}	10	10	10	10	15	15	15	15	17	17	17	17
D_{25}	**4**	**4**	**4**	**4**	**6**	**6**	**6**	**6**	**3**	**3**	**3**	**3**
D_{26}	**1**	**1**	**1**	**1**	14	14	14	14	15	16	15	15
D_{27}	**5**	**5**	**5**	**5**	**3**	**3**	**3**	**3**	**2**	**2**	**2**	**2**
D_{28}	21	21	21	21	19	19	19	19	18	18	18	18

Table 7. Ranking patterns for different *10/Low/Z/1/α* combinations

	Z=2				Z=4				Z=6			
DMU	**α=0.55**	**α=0.60**	**α=0.65**	**α=0.67**	**α=0.55**	**α=0.60**	**α=0.65**	**α=0.67**	**α=0.55**	**α=0.60**	**α=0.65**	**α=0.67**
D01	19	19	20	19	23	23	23	23	19	19	19	19
D02	20	20	19	19	21	21	21	21	17	17	17	17
D03	21	21	21	21	18	17	17	17	2	2	2	2
D04	10	10	10	10	19	19	19	19	18	18	18	18
D05	15	15	15	15	2	2	2	2	8	8	8	8
D06	7	7	7	7	1	1	1	1	1	1	1	1
D07	18	18	18	18	16	16	16	16	24	24	24	24
D08	11	11	11	11	9	9	9	9	8	8	8	8
D09	4	4	4	4	14	14	14	14	7	7	7	7
D10	26	26	26	26	22	22	22	22	20	20	20	20
D11	9	9	9	9	4	4	4	4	3	3	3	3
D12	24	24	24	24	24	24	24	24	25	25	25	25
D13	13	13	13	13	10	10	10	10	15	15	15	15
D14	17	17	17	17	12	12	12	12	12	12	12	12
D15	16	16	16	16	8	8	8	8	5	5	5	5
D16	27	27	27	27	28	28	28	28	28	28	28	28
D17	25	25	25	25	26	26	26	26	27	27	27	27
D18	14	14	14	14	7	7	7	7	10	10	10	10
D19	28	28	28	28	27	27	27	27	26	26	26	26
D20	5	5	5	5	25	25	25	25	16	16	16	16
D21	22	22	22	22	20	20	20	20	23	23	23	23
D22	3	3	3	3	6	6	6	6	11	11	11	11
D23	12	12	12	12	5	5	5	5	3	3	3	3
D24	2	2	2	2	3	3	3	3	6	6	6	6
D25	8	8	8	8	13	13	13	13	14	14	14	14
D26	1	1	1	1	15	15	15	15	21	21	21	21
D27	6	6	6	6	11	11	11	11	13	13	13	13
D28	23	23	23	23	17	18	18	18	22	22	22	22

Tables 6 and 7 divulge that full ranking is accomplished for all DRs, without any tight rank. In the event of tight ranks, priority is given to the DR whose self-efficiency score is the best. If both tight rank DRs are equally efficient, ranks are assigned arbitrarily.

It is important to note that the variation of the optimistic value α does not affect the structure of the ranking patterns for any *10/A/Z/ε/α* instance. Indeed, the ranking patterns are rather stable. As such, the proposed ranking procedure is not affected by the subjectivity of the DM, which advocates strongly in favour of its robustness.

The highlighted rows in Table 6 show that the leading positions are occupied by 8 out of 10 efficient DRs regardless of the values of Z and α in instances *10/Low/Z/0/α*. A comprehensive overview of the proportions of efficient DRs among leading DRs all over *10/A/Z/ε/α* instances is shown in Figure 3.

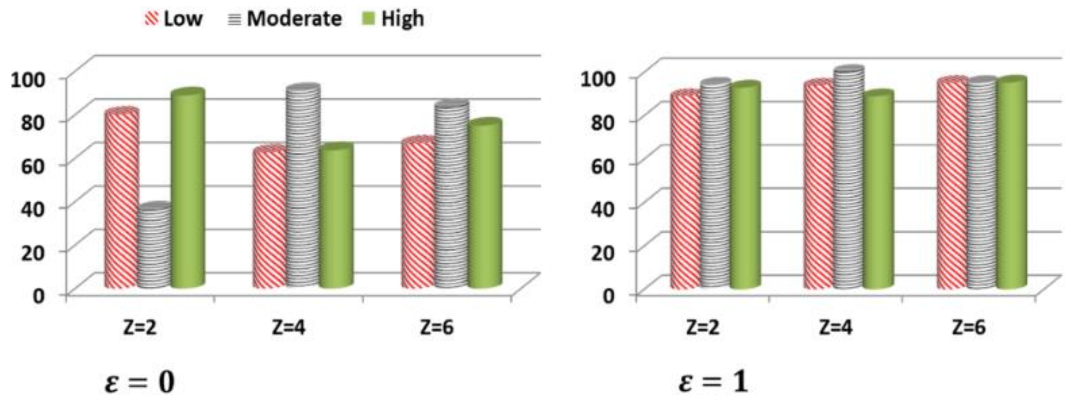

Fig. 3. Proportions of efficient dispatching rules in leading positions.

Apparently, the outcomes of the ranking approach exhibit deep dissimilarities depending on whether energy costs are part of the evaluation process. Indeed, the proportion of energy-efficient DRs that are found in leading positions varies between 88.89% and 100%. When energy costs are ignored, the ranking approach captures as low as 36.36% of the efficient DRs only. This suggests that the potential of the ranking approach to preserve the benchmarking status of efficient DRs while trying to enhance discrimination is more pronounced with job shop instances for which energy costs matter.

The top DRs yield for each *10/A/Z/ε/α* instance are presented in Table 8.

Table 8. Top dispatching rules for *10/A/Z/ε* instances

	Congestion level A	Z=2	Z=4	Z=6
ε=0	Low	WINQ	COVERT10	COVERT10
	Medium	COVERT10	WINQ	ATC10
	High	WINQ	WINQ	WINQ
ε=1	Low	WINQ	COVERT10	COVERT10
	Medium	WINQ	WINQ	ATC10
	High	WINQ	WINQ	WINQ

The results in Table 8 offer an indication that the top performing DRs are unaffected whether or not the total energy cost criterion is taken into consideration. This suggests a robustness in these DRs that extends to TEC minimization. On the other hand, the energy-oriented DRs conspicuously occupy ranks among the bottom half of the 28 DRs, even though they are by far the best performers when the total energy cost is considered on its own. Apart from these DRs that are customized for the TEC, the WINQ rule outperforms the other 'traditional' DRs in minimizing TEC, in the great majority of the test categories. This fact further supports the validity of the DR rankings produced by the DEA-based framework that has been proposed in this paper. It is not readily apparent why the WINQ rule outperforms the traditional

rules for TEC minimization. One possibility is that this rule, by its nature, tends to minimize machine starvation, resulting in less idle times. Considering that half of the working day is covered by the off-peak pricing, a better machine utilization during this period could offset the increased costs of higher utilizations during the peak period, which constitutes only 25% of the working day.
Table 9 presents the best ranked energy-oriented DRs.

Table 9. Best ranked energy-oriented dispatching rules for *10/A/Z/ε* instances

	Congestion level A	Z=2		Z=4		Z=6	
		DR	Rank	DR	Rank	DR	Rank
ε=0	Low	F-COVERT	9	Fit-LWK	4	Fit-LWK	9
	Medium	Fit+SLSM	3	LTOUC	6	Fit-LWK	13
	High	Fit+SLSS	12	Fit-pxe	10	Fit-pxe	10
ε=1	Low	Fit+SLSS	2	Fit+SLSS	3	Fit+SLSM	3
	Medium	Fit+SLSS	2	Fit+SLSS	3	Fit-pxe	3
	High	Fit+SLSS	2	Fit+SLSS	2	Fit+SLSS	6

The low rankings of the energy-oriented DRs is not a surprise, because these rules focus on only one of the eight performance objectives, in particular, the objective that conflicts the most with the others. Meanwhile, SLSS appears as the top-ranked DR in most of the cases where energy costs are considered (ε=1). Although this rule is one of the weakest among the energy-oriented DRs in minimizing TEC, it appears to provide the best trade-off in TEC against improved performance in the other seven performance objectives. The extent of this trade-off, compared to WINQ, diminishes with decreased shop congestion and slower job arrival rates.

5.3. Effect of energy on ranking

Does energy affect seriously the ranking of the DRs? To answer this question, we compare the ranking patterns produced for each *10/A/Z/0* instance with their counterparts in *10/A/Z/1* instances.
Over all the ranking patterns, there are 19.84% similar rank positions. As exhibited in Figure 4, the maximum number of similarities occurs for 10 DRs in both low and high congestions for different due-date tightness levels, *Z*=4 and *Z*=6, respectively.

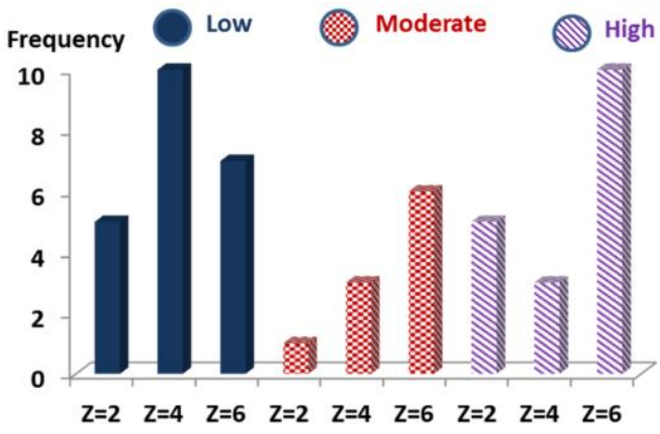

Fig. 4. Frequency of same rank positions.

In the meantime, the lowest proportion of similar rank positions is detected within moderate congestion instances for a total of 10 DRs out of 84, and a single similarity noted for the due-date tightness level *Z*=4.

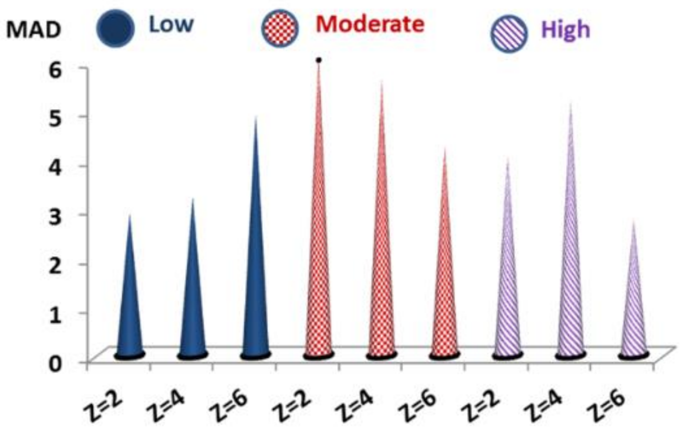

Fig. 5. Mean Average Deviations of rank positions.

Figure 5 shows that the gaps separating the rank positions of the same DR under *10/A/Z/0* and *10/A/Z/1* instances vary, on average, between 3 and 6 places, with the deepest gaps revealed for moderate congestion.
These results stress the fact that the DRs' ranking patterns are dissimilar, depending on whether energy costs are involved over the evaluation process or ignored.
In the light of the above discussion, energy appears to be a determinant factor in the ranking process and, hence, the selection of the best DR, whatever the characteristics of the job shop or the attitude of the DM.

5.4. Statistical analysis of the ranking

An important issue that also needs to be examined is the effect on the DRs' ranking patterns of the application of another ranking approach. In order to investigate this issue, one alternative is the ranking method presented in Oukil & El-Bouri (2021) for ranking DRs in a flow shop environment. The latter method, which is referred as M2, ranks the DRs by using exclusively aggregate CE scores, as opposed to the ranking procedure proposed in this paper (let's denote it M1), which adopts aggregate votes.

As such, method M2 is run with the instances *10/A/Z/1* for different congestion levels $A \in$ {Low, Moderate, High} and due date tightness $Z \in \{2, 4, 6\}$. The ranking patterns produced with both methods M1 and M2 are presented in Table 10.

Table 10. Ranking patterns for *10/A/Z/1* instances with methods M1 and M2

A	Low						Medium						High					
Z	**2**		**4**		**6**		**2**		**4**		**6**		**2**		**4**		**6**	
DR	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**
D01	19	17	23	19	19	6	17	17	21	13	9	13	16	17	24	8	19	17
D02	19	10	21	14	17	4	18	14	18	12	16	10	14	16	14	4	5	19
D03	21	13	17	10	2	7	21	15	7	10	**1**	**8**	15	9	3	2	3	21
D04	10	6	19	17	18	5	11	13	12	14	10	18	8	7	9	15	10	16
D05	15	12	**2**	**1**	**8**	**1**	8	12	2	8	6	16	6	4	4	3	16	9
D06	7	8	**1**	**2**	**1**	**2**	12	11	6	9	7	11	3	5	**8**	**1**	9	8
D07	18	26	16	28	24	28	14	22	17	27	24	27	17	26	22	28	25	28
D08	11	20	9	18	8	17	9	19	8	16	13	21	10	20	6	18	11	10
D09	4	19	14	25	7	3	6	21	14	22	2	24	4	19	7	23	**2**	**1**
D10	26	22	22	23	20	15	23	24	13	21	21	20	22	24	17	20	8	13
D11	9	9	4	3	3	11	16	7	10	4	11	6	18	11	12	9	13	4
D12	24	24	24	24	25	19	26	26	19	26	23	23	25	25	26	25	22	18
D13	13	21	10	20	15	18	24	20	27	19	26	22	11	21	10	19	28	15
D14	17	14	12	6	12	13	20	6	23	6	14	4	20	15	11	11	21	7
D15	16	15	8	5	5	10	13	5	4	3	3	3	19	12	5	7	7	3
D16	27	27	28	27	28	26	27	28	28	28	28	28	27	28	28	27	27	25
D17	25	25	26	22	27	25	25	25	26	23	25	25	26	22	25	24	24	22
D18	14	16	7	7	10	14	7	3	5	2	5	5	23	13	21	12	23	6
D19	28	28	27	26	26	16	28	27	24	24	20	19	28	27	23	22	15	14
D20	5	4	25	12	16	23	4	8	16	18	19	15	9	6	19	17	17	24
D21	22	23	20	21	23	27	22	23	25	25	27	26	24	23	27	26	26	27
D22	**3**	**1**	6	8	11	8	3	9	9	11	22	9	7	3	20	5	12	20
D23	12	11	4	4	3	12	14	4	10	5	11	7	12	10	12	10	13	5
D24	2	5	3	9	6	21	2	2	3	7	8	2	2	2	2	13	6	11
D25	8	7	13	15	14	24	10	16	15	20	17	17	5	14	15	21	18	26
D26	**1**	**2**	15	13	21	22	**1**	**1**	**1**	**1**	**4**	**1**	**1**	**1**	**1**	**6**	**1**	**2**
D27	6	3	11	11	13	20	5	10	22	17	18	12	13	8	18	16	20	23
D28	23	18	18	16	22	9	19	18	20	15	15	14	21	18	16	14	4	12

A first look at the pairs (M1,M2) of ranking patterns indicates that there is seemingly a difference between the outcomes of the two methods, though the leading DRs appear to be similar for some instances, such as *10/Medium/2/1, 10/Medium/4/1* and *10/Medium/2/1,* or close to each other, with a shift of one or two positions, like the cases of low congestion instances *10/Low/Z/1* and instance *10/High/6/1.* With these only exceptions, no plausible conclusion could be stated regarding the overall difference between pairs of ranking patterns. Do the ranking patterns indicate that methods M1 and M2 are significantly different in terms of ranking the DRs?
To substantiate the significance of such a difference, we need to conduct a Wilcoxon signed rank test for each pair of ranking patterns (M1,M2). Hence, the following hypotheses will be tested

H_o: The two methods produce identical ranking patterns

The results of the statistical tests are displayed in Table 11, where T+ and T- represent the sum of ranks associated to positive and negative differences, respectively.

Table 11. Results of the Wilcoxon signed rank test

A	Low			Medium			High		
Z	2	4	6	2	4	6	2	4	6
T+	116	134.5	194.5	134.5	142.5	116	142	183.5	200.5
T-	160	165.5	211.5	141.5	157.5	137	183	194.5	205.5
Mean	138	150	203	138	150	126.5	162.5	189	203
Std dev	32.88	35.00	43.91	32.88	35.00	30.80	37.17	41.62	43.91
p-value	0.2517	0.3289	0.4233	0.4576	0.4152	0.3666	0.2906	0.4474	0.4773

The large p-values shown in the last row of the table suggest that, at a significance level α=0.05, there is not enough evidence to reject H_o. Consequently, we can conclude that, statistically, there is not a significant difference between the ranking patterns produced by methods M1 and M2.

6. Conclusion

Energy-efficient scheduling with multiple objectives is a problem that has hardly ever been investigated in the literature, though extremely important for mitigating emissions and enhancing sustainable operations.
In this paper, the energy-efficient scheduling problem is addressed in a dynamic job shop production environment through selection of the most energy-efficient dispatching rule (DR). A new methodology for ranking DRs with multiple objectives has been presented, with energy costs as a major performance criterion. The new approach, based on data envelopment analysis (DEA) cross-efficiency (CE), exploits the preference voting system embedded under the CE matrix to derive a collective importance scale for the aggregation process, so that to enable more robust ranking

patterns and dilute potential discrepancies resulting from cases where same number of votes is produced with different CE scores. The concept of aggregate vote has been introduced as a substitute to aggregate score.

The DEA-based framework was tested for a dynamic 10 machine jobshop production system, taking into account a TOU electricity pricing regime that consists of peak, mid-peak and off-peak prices. Jobs processed in the shop are assumed to have different power requirements, so that the total energy costs depend on the pricing period a job is worked on. In addition to minimizing the total energy costs, an additional seven scheduling objectives are applied, with the goal of minimizing performance measures in each. Scheduling of the jobs, which arrive at random points in time, is managed through the application of DRs. A total of 28 DRs were evaluated, including nine new rules formulated specifically for energy cost minimization. The proposed ranking methodology was implemented both with inclusion of the total energy cost objective, and without. The results showed that the presence of the energy costs as a criterion had a notable effect on the ranking patterns generated. Besides, the derived rankings suggested that the work-in-the-next-queue (WINQ) DR is the most favorable in the majority of the cases tested, both with and without the consideration of energy costs. Of the nine new energy-oriented DRs that were considered, the SLSS rule ranked top in most of the test cases, reflecting its capacity for better tradeoff of TEC in favor of improved performance in the other performance objectives.

The results from this research offer some possible directions for future investigations and study. Obviously, the total energy cost objective strongly conflicts with most, if not all, the other criteria. This is no better illustrated than the low rankings achieved by the energy-oriented DRs. Nevertheless, those overall rankings can help in identifying a number of candidate rules that can be explored further for hybridization with the energy-oriented rules of Table 2. Hybrid or composite DRs have a potential to boost performance for the energy criterion, with improved tradeoffs versus the other criteria.

On the methodological side, robust DEA models can be considered as a further research direction (e.g., Toloo & Mensah, 2019; Tavana *et al*. 2021).

References

Abolghasem, S. , Toloo, M. , & Amézquita, S. (2019). Cross-efficiency evaluation in the presence of flexible measures with an application to healthcare systems. *Health care management science*, *22*(3), 512-533.

Ali, A. I. , & Seiford, L. M. (1990). Translation invariance in data envelopment analysis. *Operations research letters*, *9*(6), 403-405.

Al-Mezeini, N. Oukil, A. , & Al-Ismaili, A. (2020). Investigating the efficiency of greenhouse production in Oman: A two-stage approach based on Data Envelopment Analysis and double bootstrapping. *Journal of Cleaner Production*, 247, 119160. In press. https://doi.org/10. 1016/j. jclepro. 2019. 119160

Amin, G. R. , & El-Bouri, A. (2018). A minimax linear programming model for dispatching rule selection. *Computers & Industrial Engineering*, *121*, 27-35.

Amin, G. R. , & Oukil, A. (2019). Gangless cross-evaluation in DEA: an application to stock selection. *RAIRO-Operations Research*, *53*(2), 645-655.

Angiz, M. Z. , Mustafa, A. , &Kamali, M. J. (2013). Cross-ranking of decision making units in data envelopment analysis. *Applied Mathematical Modelling*, *37*(1-2), 398-405.

Arabi, B. , Munisamy, S. , Emrouznejad, A. , Toloo, M. , & Ghazizadeh, M. S. (2016). Eco-efficiency considering the issue of heterogeneity among power plants. *Energy*, *111*, 722-735.

Ashok, S. (2006). Peak-load management in steel plants. *Applied energy*, *83*(5), 413-424.

Babu, C. A. , & Ashok, S. (2008). Peak load management in electrolytic process industries. *IEEE Transactions on Power Systems*, *23*(2), 399-405.

Baker, K. R. (1974). *Introduction to sequencing and scheduling*. John Wiley & Sons.

Banker, R. D. , Charnes, A. , & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, *30*(9), 1078-1092.

Biel, K. , & Glock, C. H. (2016). Systematic literature review of decision support models for energy-efficient production planning. *Computers & Industrial Engineering*, 101, 243-259.

Braglia, M. , &Petroni, A. (1999). Data envelopment analysis for dispatching rule selection. *Production planning & control*, *10*(5), 454-461.

Castro, P. M. , Harjunkoski, I. , & Grossmann, I. E. (2011). Optimal scheduling of continuous plants with energy constraints. *Computers & Chemical Engineering*, *35*(2), 372-387.

Castro, P. M. , Sun, L. , &Harjunkoski, I. (2013). Resource–task network formulations for industrial demand side management of a steel plant. *Industrial & Engineering Chemistry Research*, *52*(36), 13046-13058.

Chang, Y. L. , Sueyoshi, T. , & Sullivan, R. S. (1996). Ranking dispatching rules by data envelopment analysis in a job shop environment. *IIE transactions*, *28*(8), 631-642.

Charnes, A. , Cooper, W. W. , & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429-444.

Cheng, J. , Chu, F. , & Zhou, M. (2017). An improved model for parallel machine scheduling under time-of-use electricity price. *IEEE Transactions on Automation Science and Engineering*, *15*(2), 896-899.

Chiang, T. & Fu, L. (2007). Using dispatching rules for job shop scheduling with due-date based objectives. *International Journal of Production Research*, *45*, 3245–3262.

Cook, W. D. , Tone, K. , & Zhu, J. (2014). Data envelopment analysis: Prior to choosing a model. *Omega*, *44*, 1-4.

Cooper, W. W. , Seiford, L. M. , & Tone, H. (2002). *Data envelopment analysis: A comprehensive text with models, applications, references, and DEA-Solver software*. New York: Kluwer Academic Publisher.

Ding, J. Y. , Song, S. , Zhang, R. , Chiong, R. , & Wu, C. (2015). Parallel machine scheduling under time-of-use electricity prices: New models and optimization approaches. *IEEE Transactions on Automation Science and Engineering*, *13*(2), 1138-1154.

Dong, C. , Ng, C. T. & Cheng, T. C. E. (2017). Electricity time-of-use tariff with stochastic demand. *Production and operations management*, *26(1)*, 64-79.

El Bouri, A. , & Amin, G. R. (2015). A combined OWA–DEA method for dispatching rule selection. *Computers & Industrial Engineering*, 88, 470-478.

Emrouznejad, A. (2014). Advances in data envelopment analysis. *Annals of Operations Research*, 214(1), 1-4.

Emrouznejad, A. , & Marra, M. (2014). Ordered weighted averaging operators 1988–2014: A citation-based literature survey. *International Journal of Intelligent Systems*, 29, 994-1014.

Emrouznejad, A. , & Yang, G. L. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences*, 61, 4-8.

Fernandez, M. , Li, L. , & Sun, Z. (2013). "Just-for-Peak" buffer inventory for peak electricity demand reduction of manufacturing systems. *International Journal of Production Economics*, 146(1), 178-184.

Gahm, C. , Denz, F. , Dirr, M. , &Tuma, A. (2016). Energy-efficient scheduling in manufacturing companies: A review and research framework. *European Journal of Operational Research*, *248*(3), 744-757.

Hassan, M. M. , & Oukil, A. (2021). Design of efficient systems of commercial material handling equipment for supply chain and logistics facilities using DEA. *International Journal of Logistics Systems and Management*, 39(2), 241-272.

He, Y. , Li, Y. , Wu, T. , & Sutherland, J. W. (2015). An energy-responsive optimization method for machine tool selection and operation sequence in flexible machining job shops. *Journal of Cleaner Production*, *87*, 245-254.

Jiang, T. , Zhang, C. , Zhu, H. , Gu, J. , & Deng, G. (2018). Energy-efficient scheduling for a job shop using an improved whale optimization algorithm. *Mathematics*, *6*(11), 220.

Kurniawan, B. , Gozali, A. A. , Weng, W. , & Fujimura, S. (2017, December). A genetic algorithm for unrelated parallel machine scheduling minimizing makespan cost and electricity cost under time-of-use (TOU) tariffs with job delay mechanism. In *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (pp. 583-587). IEEE.

Liang, P. , Chen, W. , Luo, M. , He, W. , & Liu, G. (2019a). Job-shop scheduling problem considering power cost and makespan under time-of-use electricity price. *Journal of Computational Methods in Sciences and Engineering*, *19*(4), 929-941.

Liang, J. , Wang, Y. , Zhang, Z. H. , & Sun, Y. (2019b). Energy efficient production planning and scheduling problem with processing technology selection. *Computers & Industrial Engineering*, 132, 260-270.

Lovell, C. K. , & Pastor, J. T. (1999). Radial DEA models without inputs or without outputs. *European Journal of operational research*, *118*(1), 46-51.

Luo, H. , Du, B. , Huang, G. Q. , Chen, H. , & Li, X. (2013). Hybrid flow shop scheduling considering machine electricity consumption cost. *International Journal of Production Economics*, *146*(2), 423-439.

Masmoudi, O. , Yalaoui, A. , Ouazene, Y. , &Chehade, H. (2017). Solving a capacitated flow-shop problem with minimizing total energy costs. *The International Journal of Advanced Manufacturing Technology*, *90*(9-12), 2655-2667.

Mitra, S. , Grossmann, I. E. , Pinto, J. M. , & Arora, N. (2012). Optimal production planning under time-sensitive electricity prices for continuous power-intensive processes. *Computers & Chemical Engineering*, *38*, 171-184.

Moon, J. Y. , & Park, J. (2014). Smart production scheduling with time-dependent and machine-dependent electricity cost by considering distributed energy resources and energy storage. *International Journal of Production Research*, *52*(13), 3922-3939.

Navas, L. P. , Montes, F. , Abolghasem, S. , Salas, R. J. , Toloo, M. , & Zarama, R. (2020). Colombian higher education institutions evaluation. *Socio-Economic Planning Sciences*, *71*, 100801.

Oral, M. , Amin, G. R. , & Oukil, A. (2015). Cross-efficiency in DEA: A maximum resonated appreciative model. *Measurement*, *63*, 159-167.

Oral, M. , Oukil, A. , Malouin, J. L. , & Kettani, O. (2014). The appreciative democratic voice of DEA: A case of faculty academic performance evaluation. *Socio-Economic Planning Sciences*, *48*(1), 20-28.

Oukil, A. (2018). Ranking via composite weighting schemes under a DEA cross-evaluation framework. *Computers & Industrial Engineering*, *117*, 217-224.

Oukil, A. (2019). Embedding OWA under preference ranking for DEA cross-efficiency aggregation: Issues and procedures. *International Journal of Intelligent Systems*, *34*(5), 947-965.

Oukil, A. , & Al-Zidi, A. (2018). Benchmarking the hotel industry in Oman through a three-stage DEA based procedure. *Journal of Arts & Social Sciences*, *9*(2), 5-23.

Oukil, A. , & Amin, G. R. (2015). Maximum appreciative cross-efficiency in DEA: A new ranking method. *Computers & Industrial Engineering*, *81*, 14-21.

Oukil, A. , & Govindaluri, S. M. (2017). A systematic approach for ranking football players within an integrated DEA-OWA framework. *Managerial and Decision Economics*, *38*(8), 1125-1136.

Oukil, A. , & Govindaluri, S. M. (2020). A hybrid multi-attribute decision-making procedure for ranking project proposals: A historical data perspective. *Managerial and decision economics*, 41(3), 461-472.

Oukil, A. (2020). Exploiting value system multiplicity and preference voting for robust ranking. *Omega*, 94, 102048. https://doi. org/10. 1016/j. omega. 2019. 03. 006.

Oukil, A. (2020). Designing efficient material handling systems: a two-stage approach based on DEA cross-efficiency. In *2020 5th International Conference on Logistics Operations Management (GOL)* (pp. 1-5). IEEE.

Oukil, A. , & El-Bouri, A. (2021). Ranking dispatching rules in multi-objective dynamic flow shop scheduling: a multi-faceted perspective. *International Journal of Production Research*, 59 (2), 388-411.

Oukil, A. , Soltani, A. A. , Boutaghane, H. , Abdalla, O. , Bermad, A. , Hasbaia, M. , & Boulassel, M. R. (2021). A Surrogate Water Quality Index to assess groundwater using a unified DEA-OWA framework. *Environmental Science and Pollution Research*, 1-28.

Pach, C. , Berger, T. , Sallez, Y. , Bonte, T. , Adam, E. , & Trentesaux, D. (2014). Reactive and energy-aware scheduling of flexible manufacturing systems using potential fields. *Computers in Industry*, *65*(3), 434-448.

Pastor, J. T. , & Aparicio, J. (2015). Translation invariance in data envelopment analysis. In *Data envelopment analysis* (pp. 245-268). Springer, Boston, MA.

Saeidi, R. G. , Oukil, A. , Amin, G. R. , & Raissi, S. (2015). Prioritization of textile fabric defects using ordered weighted averaging operator. *The International Journal of Advanced Manufacturing Technology*, *76*(5-8), 745-752.

Seiford, L. M. , & Zhu, J. (2002). Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research*, 142(1), 16-20.

Sels, V. , Gheysen, N. , & Vanhoucke, M. (2012). A comparison of priority rules for the job shop scheduling problem under different flow time-and tardiness-related objective functions. *International Journal of Production Research*, *50*(15), 4255-4270.

Sexton, T. R. , Silkman, R. H. , & Hogan, A. J. (1986). Data envelopment analysis: Critique and extensions. In *Measuring Efficiency: An Assessment of Data Envelopment Analysis*. R. H. Silkman Eds. San Francisco, CA: Jossey Bass.

Shrouf, F. , Ordieres-Meré, J. , García-Sánchez, A. , & Ortega-Mier, M. (2014). Optimizing the production scheduling of a single machine to minimize total energy consumption costs. *Journal of Cleaner Production*, *67*, 197-207.

Soltani, A. A. , Oukil, A. , Boutaghane, H. , Bermad, A. , & Boulassel, M. R. (2021). A new methodology for assessing water quality, based on data envelopment analysis: Application to Algerian dams. *Ecological Indicators*, 121, 106952.

Sow, O. , Oukil, A. , Ndiaye, B. M. , & Marcos, A. (2016). Efficiency analysis of public transportation subunits using DEA and Bootstrap Approaches–Dakar Dem Dikk case study. *Journal of Mathematics Research*, 8(6), 114-127.

Sun, Z. , Li, L. , Fernandez, M. , & Wang, J. (2014). Inventory control for peak electricity demand reduction of manufacturing systems considering the tradeoff between production loss and energy savings. *Journal of Cleaner Production*, *82*, 84-93.

Tan, Y. Y. , Huang, Y. L. , & Liu, S. X. (2013). Two-stage mathematical programming approach for steelmaking process scheduling under variable electricity price. *Journal of Iron and Steel Research International*, *20*(7), 1-8.

Tavana, M. , Toloo, M. , Aghayi, N. , & Arabmaldar, A. (2021). A robust cross-efficiency data envelopment analysis model with undesirable outputs. *Expert Systems with Applications*, 167, 114117.

Tigane, M. , Dahane, M. , &Boudhar, M. (2019). Multiobjective approach for deteriorating jobs scheduling for a sustainable manufacturing system. *The International Journal of Advanced Manufacturing Technology*, *101*(5-8), 1939-1957.

Toloo, M. , & Mensah, E. K. (2019). Robust optimization with nonnegative decision variables: A DEA approach. *Computers & Industrial Engineering*, 127.

Toloo, M. , & Tavana, M. (2017). A novel method for selecting a single efficient unit in data envelopment analysis without explicit inputs/outputs. *Annals of Operations Research*, 253(1), 657–681.

Wang, Y. M. , & Chin, K. S. (2011). The use of OWA operator weights for cross-efficiency aggregation. *Omega*, *39*(5), 493-503.

Wang, Y. M. , &Parkan, C. (2005). A minimax disparity approach for obtaining OWA operator weights. *Information Sciences*, *175*(1-2), 20-29.

Wang, Y. , & Li, L. (2013). Time-of-use based electricity demand response for sustainable manufacturing systems. *Energy*, *63*, 233-244.

Yager, R. R. (1988). On ordered weighted averaging aggregation operators in multicriteria decisionmaking. *IEEE Transactions on systems, Man, and Cybernetics*, *18*(1), 183-190.

Yager, R. R. (1995). An approach to ordinal decision making. *International Journal of Approximate Reasoning*, *12*(3-4), 237-261.

Yusta, J. M. , Torres, F. , &Khodr, H. M. (2010). Optimal methodology for a machining process scheduling in spot electricity markets. *Energy Conversion and Management*, *51*(12), 2647-2654.

Zhang, H. , Zhao, F. , Fang, K. , & Sutherland, J. W. (2014). Energy-conscious flow shop scheduling under time-of-use electricity tariffs. *CIRP Annals*, *63*(1), 37-40.

Zhang, L. , Tang, Q. , Wu, Z. , Wang, F. (2017). Mathematical modeling and evolutionary generation of rule sets for energy-efficient flexible job shops. *Energy*, 138, pp. 210-227.

Zhou, S. , Jin, M. , Du, N. (2020). Energy-efficient scheduling of a single batch processing machine with dynamic job arrival times. *Energy*, 209, art. no. 118420.