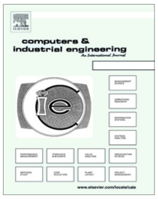
Computers & Industrial Engineering 88 (2015) 470–478

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie



A combined OWA–DEA method for dispatching rule selection

Ahmed El Bouri, Gholam R. Amin *

Department of Operations Management and Business Statistics, College of Economics and Political Science, Sultan Qaboos University, Oman

A R T I C L E I N F O

Article history:
Received 26 July 2014
Received in revised form 27 May 2015
Accepted 17 August 2015
Available online 24 August 2015

Keywords:
Dispatching rules
Ordered weighted averaging
Data envelopment analysis
Flowshop
Scheduling

A B S T R A C T

Dispatching rule selection is an important issue in dynamic scheduling of production systems. When there are multiple performance criteria, identification of the most efficient dispatching rule is not an easy task. This paper considers an ordered weighted averaging (OWA) methodology combined with a data envelopment analysis (DEA) model for identifying the best dispatching rule in a flowshop environment. Standard DEA cannot be used directly, due to ambiguity in the inputs and outputs that may be specified in the flowshop scheduling problem. To overcome this drawback, an OWA method is used to first assess the dispatching rules, measured in terms of multiple factors, for different decision making optimism levels. This is followed by using a DEA model to aggregate the OWA assessments, in order to identify the dispatching rule(s) with the best overall performance. A computational analysis is performed by using randomly generated test problems, and different scenarios involving different factor priorities. The results demonstrate that the proposed OWA–DEA approach successfully identifies which dispatching rules are efficient, and which are not.

1. Introduction

Dispatching rules are used to prioritize jobs that are queued for processing on a machine. They are a simple and frequently effective tool for scheduling the processing of jobs in a production system, particularly when it is a dynamic one where new jobs continually arrive and join the other jobs currently in the system. The order in which the queued jobs are processed on the machines in a multi-machine shop affects the average job completion times, machine idle times, percentages of jobs completed on time, and other performance measures. The scheduling objectives are usually to optimize performance with regard to one or more of these measures. A decision problem arises whenever a machine becomes available to start processing a new job, and there is more than one job waiting in queue for that machine. That decision is settled according to the dispatching rule. There are numerous different dispatching rules, and the performance of the production system in respect of the different performance criteria varies based on the dispatching rule that is used. One dispatching rule could be very effective for one performance criterion, but quite poor for another criterion. This raises difficulties when the scheduling objectives are to maximize performance in more than one criterion. In such a multi-criteria environment, the scheduling problem becomes that of selecting the dispatching rule which best satisfies the set of given performance criteria as a whole.

If the different performance measures that result from applying a particular dispatching rule are considered as system outputs, then the possibility of using a data envelopment analysis (DEA) approach to find which of the dispatching rules are efficient could be investigated. There are a few studies in the literature that have discussed the problem of dispatching rule selection in a job shop scheduling by means of DEA, such as Chang, Toshiyuki, and Sullivan (1996), and Braglia and Petroni (1999). These studies modeled each dispatching rule in terms of multiple (good) inputs and multiple (good) outputs.

The standard production theory in DEA assumes that producing more outputs and consuming less inputs as a criterion in performance evaluation of decision making units (DMUs). A DMU with less input consumption and/or more output production than the other DMUs has higher efficiency score. This basic assumption in production theory holds when all of the inputs and outputs are recognized as good variables, concluding that in the presence of a bad input and/or output the standard DEA models fail to fairly evaluate the DMUs. For instance in the dispatching rule selection using DEA suggested in Braglia and Petroni (1999), there are three outputs: (i) in-process waiting time, (ii) idle time, and (iii) queue time. There are also two inputs related to the costs of dispatching rules. The three defined outputs cannot be viewed as good outputs because increasing these factors will not lead to an efficiency improvement. On the contrary, a dispatching rule with less in-process, idle and

---

* Corresponding author. Tel.: +968 24142910; fax: +968 24413977.
E-mail address: gamin@squ.edu.om (G.R. Amin).

http://dx.doi.org/10.1016/j.cie.2015.08.007
0360-8352/

queue times is more efficient than any other dispatching rule when their implementation costs, or the two defined inputs, are the same. In this case even normalization of outputs, as used in Braglia and Petroni (1999), would not produce valid DEA results. In fact, even such a normalized output is still not a good output, and hence a standard DEA model cannot be used for evaluation. As a result, the dispatching rules identified by the standard DEA model are not necessarily the best performing ones when there is at least one such output and/or input. The same drawback exists in the study of Chang et al. (1996), where the two defined outputs namely *maximum completion time* (*makespan*) and *mean tardiness* are viewed as two inputs. Thus, a direct application of DEA is unlikely to produce a valid result. However, a pre-processing phase can be implemented by using an ordered weighting average (OWA) operator to evaluate the dispatching rules for different decision maker's optimism levels, and computing multiple scores for each rule. After that has been done, a DEA model can be used for aggregation and identification of the efficient dispatching rule(s).

The present research study is organized as follows. Section 2 discusses in further detail the difficulty of using DEA for dispatching rule selection, while Section 3 provides the research background and a literature review based on OWA and DEA methods. A computational analysis involving the use of dispatching rules in a five-machine flowshop is covered in Section 4, with a discussion of the results in Section 5. Finally, the study's concluding remarks are presented in Section 6.

2. Basic concept: illustration

The major drawback of using DEA for dispatching rules selection is due to the identification of appropriate inputs and outputs in DEA. In fact, DEA is a successful method when DMUs can be viewed as production systems where multiple inputs, as resources, are consumed to produce multiple outputs as products, as discussed recently in Cook, Tone, and Zhu (2014). However, some factors are often neither inputs nor outputs. In this case using DEA cannot produce valid rankings. To see this, we use the same example introduced in Chang et al. (1996). Assume there are five dispatching rules, as DMUs, denoted by A to E. Each dispatching rule is measured in terms of three factors namely *maximum completion time* (*makespan*), denoted by C_{max}, the *mean tardiness*, denoted by $\bar{T}$, and *computation time*. Fig. 1 shows the production possibility set (PPS) for the corresponding dispatching rules when $C_{\max}$ and $\bar{T}$ are considered as two outputs. Moreover, the computation time is considered as an input with the same level for all dispatching rules and therefore can be ignored from the evaluation.

According to the efficiency frontier shown in Fig. 1, the three efficient dispatching rules are A, B, and E. Moreover, two inefficient DMUs are C and D. Both inefficient dispatching rules in Fig. 1 are dominated by the dispatching rule A. This simply means that dispatching rules C and D have less makespan and less mean tardiness than that of dispatching rule A. Therefore, C and D must have better performance than dispatching rule A. As a result, the two defined factors cannot be viewed as (good) outputs, otherwise DEA evaluation does not guarantee valid result. Chang et al. (1996) supposed that $C_{\max}$ and $\bar{T}$ are two outputs, however their sketched PPS and discussion show that these two factors are actually considered as two inputs, see page 634 in Chang et al. (1996). If we assume makespan and the mean tardiness as two inputs, and the computation time as the single output, it leads to the following PPS shown in Fig. 2.

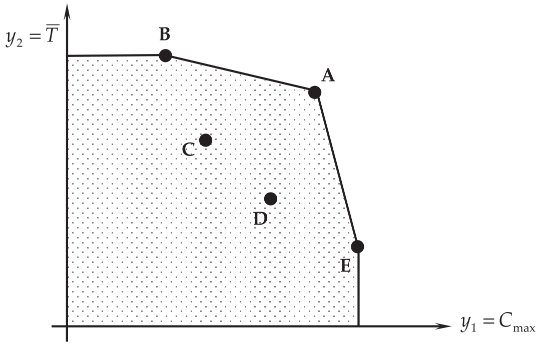


Fig. 1. PPS for five dispatching rules: two outputs.

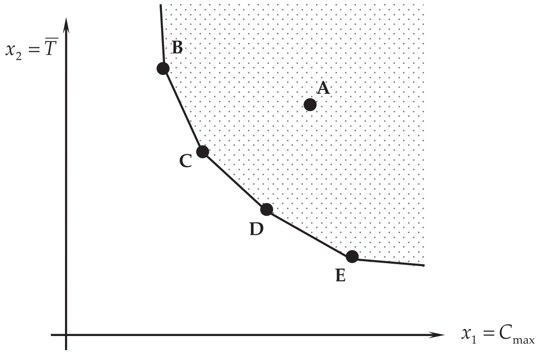


Fig. 2. PPS for five dispatching rules: two inputs.

It is worth noting that the efficient dispatching rule A in Fig. 1 is now inefficient with the PPS shown in Fig. 2. This illustration shows that selection of inputs and outputs is very important in the DEA evaluation. Consequently, the standard DEA model cannot be applied directly for evaluation of dispatching rules unless the actual inputs and outputs are well defined. This is really a difficult task when for a parameter the less-is-better value is preferred, considering also that it is neither an actual input nor an output. The same difficulty exists when the more-is-better value of a variable is preferred, considering that it, too, is neither an actual output nor an input. The same drawback exists in the work of Braglia and Petroni (1999) where a standard DEA model is used to evaluate different dispatching rules. However, the two defined inputs, the *average monetary daily value* and the *delivery delay cost*, can be viewed as the resources of dispatching rules, the outcome generated from running of the dispatching rules are not necessarily actual outputs. Braglia and Petroni (1999) considered "*in-process waiting time*", "*idle time*", and "*queue time*" as three outputs, although these cannot be really viewed as outputs because increasing these factors will not lead to an efficiency improvement. A standard DEA model for evaluation of dispatching rules with this type of outputs considers all variables as (good) outputs and therefore inevitably leads to invalid efficiency scores.

In this paper, the potential of an OWA operator is used to overcome this drawback before assessing dispatching rules by DEA. In fact, the OWA operator is proposed to evaluate dispatching rules in the presence of multiple factors, regardless of the type of the defined variable, and generates multiple good outputs for each dispatching rule. This enables DEA to be then used for aggregation and determining the best performing rule(s).

3. Research background

3.1. OWA operator

The OWA operator, introduced in Yager (1988), is an aggregation method under an uncertain environment that maps