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Routing distributions and their impact on dispatch rules ☆

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ABSTRACT

Motivated by the job-shop production process of our industry partner, we examine dispatching rules effects on two key performance indicators (KPIs) – job lateness and the percentage of late jobs. In the literature, authors use the uniform distribution to generate random job shop data. In addition to our discussion on dispatching rules, we propose an alternative idea for random job shop data, the *routing distribution*, and we compare dispatching rules performance using KPI frontiers under different routing distributions. We show that using their current dispatch rule, earliest operation due date (EODD), the industry partner is never worse off, even as their job-shop's operational environment changes. We further show that using multiple dispatch rules across several job-shop departments does improve a job-shop's performance on the KPIs, though the improvement is small and in some cases may not be statistically significant. In addition, we find that EODD is one of several dispatching rule which consistently lie on the KPI frontier for different job routing distributions. We find that dispatching rule performance is greatly affected by the routing distribution of the job-shop where the rules are employed. Lastly, we leave the readers with some insight into determining which dispatch rules and routing distributions should be considered for different job shops.

1. Introduction

Manufacturing is an important part of Canada's future economic development, representing 14% of Canada's Gross Domestic Product, but it is facing many new challenges from around the globe. To address those challenges, Canadian manufacturers need to become more efficient (CMC, 2012). Many companies, like our industry partner, are seeking efficiency gains by implementing Industrial Engineering methods in their job-shops, particularly for their production scheduling. In this paper, we show that our industry partner's current scheduling method is a fine choice, that multiple rule methods can increase the efficiency of their production scheduling further, and that, for the most part, these results generalize to other job-shops.

We analyze the job-shop scheduling method used by our industry partner by considering their two key performance indicators (KPI), percentage of late jobs and the maximum lateness across all jobs. In addition, we would like to propose the use of *human implementable* scheduling methods, methods that can be done using scheduling equipment such as work-in-progress lists, and job boards and requires no new equipment or training. To check the robustness of a method, we check how well it performs as the product line of our industry partner changes, a natural progression in their case.

Dispatching rules are a commonly used scheduling method, and most are human implementable. Recall that the production in a job-shop is organized into *jobs*: an ordered list of operations each completed using a specific machine or resource for a set amount of time. Each job has a *due date* by which time the job is ideally complete. At each machine, enqueued jobs are waiting to be processed, and a *dispatching rule* is a scheduling method used by a machine every time it finishes processing an operation, with the function to choose the next enqueued job to 'dispatch' for processing.

Dispatching rules are typically quite simple:

All else being equal, process the job with the earliest due date.

The earliest due date (EDD) rule, as this example is known, is human implementable. Our industry partner currently uses a variant of EDD called earliest operation due date (EODD) defined in Section 3.4. There are many other well-known dispatching rules; Pinedo (2009) defines several. In this paper, we consider only those dispatching rules which can be assessed using a list to ensure human implementability.

We consider using a single rule throughout the entire job-shop as well as using multiple rules for subsets of machines. The idea of

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using multiple rules originates from our industry partner that organizes their machines and production scheduling using departments. We show that the best performing of these multiple rule methods out-perform using single rule, though typically by less than 1% fewer late jobs.

We repeat this analysis by considering different *routing distributions*, a set of discrete probability distributions, each on the set of job-shop machines, with a distribution assigned to each operation of every generate job. Each operation's probability distribution is sampled to determine the machine processing that operation of every job. A simple example of a routing distribution is what we have called a uniform routing distribution, previously called an open job-shop (Philipoom & Fry, 1990), in which every probability distribution for every operation is a uniform distribution on the set of machines. As we see in this paper, the performances of our dispatching rules is very different on the uniformly generated production data compared to any other routing distribution we consider, defined in Section 3.3. We show this by plotting the KPI Pareto frontier or *KPI frontier* of each routing distribution; the KPI frontier exhibits the trade-off between the two KPIs of importance, percentage of late jobs and maximum lateness.

There are many scheduling heuristics and algorithms studied in both Operations Research, Industrial Engineering, and artificial intelligence with significantly better theoretical performance than dispatching rules. In fact, our industry partner previously scheduled their production using a computerized scheduling system. However, in McKay, Safayeni, and Buzacott (1988), the authors find that the theoretical methods studied are likely irrelevant to real job-shops, as they do not account for many of the realities faced by schedulers in real job-shops. The scheduling methods we describe here, avoid being irrelevant by: (1) being understandable, the scheduling decisions are clear and understandable by managers and schedulers, (2) being flexible in responding to the changing shop floor environment, and (3) employees are empowered to make decisions on the floor in turn increasing productivity. We would like to expand on the third point a little bit, by pointing out that while using their computer scheduling system, our industry partner experienced employees acquiescing to the schedule regardless of their better judgment, and found that employee involvement in many other aspects of production declined, negatively affecting production as a result (Industry-Partner, 2013).

In Section 3.4, we define several dispatching rules for use in our simulations either alone or in combinations. We conduct a tournament using a job-shop simulation, described in Section 3.1, and compare the performance of each simulation using two of our industry partner's KPIs: the percentage of late jobs and the maximum lateness. The simulations we seek are on the KPI frontier for these two KPIs. Our simulations are run on data provided by our industry partner, as well as random production data generated using empirical distributions based on that same data and the routing distributions defined in Section 3.3. We present the results of our simulations in Sections 4 and 5. We conclude, in Section 7.1, with a specific recommendation for both our industry partner and for job-shops in general.

2. Related work

The study of job-shop problems has proceeded similarly to other NP-hard problems. First, the problem is formulated and optimal algorithms are proposed (Manne, 1960). Later, after an NP-hardness proof is found Garey, Johnson, and Sethi (1976) for job-shops, researchers assume that all optimal algorithms for the problem have prohibitively long run-times, and researchers began developing approximation algorithms and heuristic solutions in favor of optimal algorithms. Dispatching rules, a family of heuristics for job-shops and the focus of this paper, were proposed by Panwalkar and Iskander (1977).

There are a variety of algorithms, which in theoretical terms, out perform dispatching rules such as the approximation algorithms (Shmoys, Stein, & Wein, 1994), the shifting bottle neck algorithm (Adams, Balas, & Zawack, 1988), or constraint programming methods (Nuijten & Aarts, 1996) are a few such algorithms. However, the solution of many of these algorithms are complete schedules, and as was mentioned above, McKay et al. (1988) found that, among other things, actual job-shops are prone to rapid and unpredictable change. Complete schedules implicitly assume that job-shops are more stable than occurs in reality, or at least our industry partner. Dispatching rules avoid this problem by not creating complete schedules; they merely specify what should be worked on next by a free machine or resource.

Another, more recent heuristic approach is to search through a job-shop instance's solution space to find solutions with good objective values. There is a large variety of such search algorithms: ant colony algorithms (Colorni & Dorigo, 1994; Huang & Liao, 2008); differential evolution algorithms (Pan, Tasgetiren, & Liang, 2008; Wei-ling & Jing, 2013); genetic algorithms (Yu & Liang, 2001; De Giovanni & Pezzella, 2010); local-search (Vaessens, Aarts, & Lenstra, 1994; Vela, Varela, & González, 2008); particle swarm algorithms (Sha & Hsu, 2006; Zhang & Wu, 2010), simulated annealing (Tavakkoli-Moghaddam, Khalili, & Naderi, 2008; Zhang & Wu, 2011), and tabu-search algorithms (Nowicki & Smutnicki, 2005; Armentano & Scrich, 2000). These algorithms also create complete solutions, but there is another problem, that of understanding generated schedules. The steps in these search methods may not be easily understood by job-shop schedulers.

We consider dispatching rules from several sources (Panwalkar & Iskander, 1977; Pinedo, 2009), as well as some new rules. We compare their performance in job-shop simulation using the two KPIs previously discussed. Similar analyses of dispatching rule performance on job-shop simulations can be found in Kaban, Othman, and Rohmah (2012), or Sculli and Tsang (1990). Our goal here is slightly different from those papers in that we not simply looking for the best performing rule under our chosen KPI or KPIs. Instead, we are recommending changes to our how industry partner's schedules to reduce the number of their late jobs, so we sought rules which outperform their current dispatching rule, earliest operation due date.

We also study routing distributions, defined in Section 1, as they appear to be an understudied aspect of a job-shop. Some job-shop researchers explicitly state the routing distribution used to create their random production data as in Adams et al. (1988), Shah (2004) and Ruiz and Vázquez-Rodríguez (2010), but being explicit about this does not seem to be common among researchers. Moreover, different routing distributions are known to affect the performance of dispatching rules (Philipoom & Fry, 1990).

The last new aspect of this paper is the focus on human implementable dispatching rules. To our knowledge, the studies of dispatching rules in the literature have not previously sorted the rules upon this criteria. The focus on human implementability comes from the need to make improvement recommendations to our industry partner that easily fit into their existing scheduling processes. In personal communication with our industry partner, we learned that they use an effective, human-centric scheduling process which has improved performance on all of their key performance indicators, reversing the production decreases attributed to a previously used computerized scheduling system (Industry-Partner, 2013). Their current process employs a human implemented dispatching rule, earliest operation due date first, so a different rule is conceivably an easy change to make, and one that maintains the centrality of the human scheduler along with the attendant benefits our industry partner experiences.