Trade-off Balancing in Scheduling for Flow Shop Production and Perioperative Processes

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We balance trade-offs between two fundamental and possibly inconsistent objectives, minimization of maximum completion time and minimization of total completion time, in scheduling serial processes. We use a novel approach of current and future deviations (CFD) to model the trade-offs between the two completion times. We also use weights α and β to balance trade-offs at the operation level and at the process level, respectively. Accordingly, we develop a constructive CFD heuristic, and compare its performance with three leading constructive heuristics in scheduling based on three separate datasets: 5400 small-scale instances, 120 Taillard's benchmark instances, and one-year historical records of operating room scheduling in a university hospital system. We show that minimization of maximum completion time and minimization of total completion time yield inconsistent scheduling sequences, and the two sequences are relatively uncorrelated. We also show that our CFD heuristic can balance trade-offs between these two objectives, outperform the three leading heuristics across different performance measures, and allow larger variations on two fundamental completion times. This means that trade-off balancing by our CFD heuristic enables a serial process to have a larger tolerance on variations of process performance, and keeps the process better under control. This performance improvement can be significant for flow shop scheduling in manufacturing in trading-off production and holding costs, and for operating room scheduling across the perioperative process in healthcare in trading-off hospital cost and patient waiting time.

Version: August 25, 2018

Keywords: Flow Shop Production, Perioperative Process, Scheduling, Trade-off Balancing.

1. Introduction

A serial process consists of a number of stages, workstations, machines, and/or operations that process jobs sequentially from the first to the last (Pinedo 2008). Typical examples of serial processes are a flow line with m machines for production scheduling in manufacturing

systems, and a 3-stage perioperative (periop) process for operating room (OR) scheduling in healthcare systems, with preoperative (preop), intraoperative (intraop), and postoperative (postop) stages (Ye et al. 2017, Gupta and Denton 2008). Maximum completion time (C_{max}) and total completion time ($\sum C_j$) are two fundamental performance measures in serial processes. Given an n-job m-machine instance, $C_{max} = C_{n,m}$ is the completion time of the last job n on the last machine m, and $\sum C_j = \sum_{j=1}^{n} C_{j,m}$ is the sum of completion times of all $j = 1, ..., n$ jobs on the last machine m. Flow time or average completion time ($\overline{C}$) equals $\sum C_j/n$, and thus for a fixed n, $\min(\sum C_j)$ is the same as $\min(\overline{C})$.

Minimizations of these two completion times, $\min(C_{max})$ and $\min(\sum C_j)$, drive many other performance metrics. For example, in production scheduling, utilization ($Util$) equals to the workload divided by a working period, where the workload is the sum of processing times and the working period is the difference between maximum completion time and start time. Given due dates of all jobs, d_j for $j = 1, ..., n$, tardiness is defined as $T_j = \max\{C_j - d_j; 0\}$, and earliness is defined as $E_j = \max\{d_j - C_j; 0\}$ in T'kindt and Billaut (2002). Accordingly, maximum tardiness ($\max(T_j)$) or maximum earliness ($\max(E_j)$) may relate to C_{max}, and total tardiness ($\sum T_j$) or total earliness ($\sum E_j$) may relate to $\sum C_j$ (Slowinski 1981, Kim 1995, Figueira et al. 2010). Work-in-process (WIP) inventory levels are influenced by the difference of average completion times between two adjacent machines or stages. In OR scheduling, overtime is evaluated by the difference between maximum completion time and OR block time; cost to the hospital can be a function of utilization of the periop process; and length of stay (LoS) across the periop process and post-anesthesia care unit (PACU) staffing are related to patient flow time (PtF).

Although C_{max} is included in $\sum C_j$, it is difficult to seek optimal solutions to $\min(C_{max})$ and to $\min(\sum C_j)$ because they are NP-complete problems for scheduling in a serial process with $m > 2$ (Garey et al. 1976, Hoogeveen and Kawaguchi 1999). In practice, heuristics and simple priority dispatching rules (PDRs) are used to achieve simple objectives and to seek near optimal solutions to real scheduling problems. For example, in OR scheduling, the shortest processing time (SPT) rule is recommended to smooth patient flow across the periop process, even over a genetic algorithm (Gul et al. 2011), and the longest processing time (LPT) rule is recommended to improve OR utilization (Magerlein and Martin 1978). In flow shop production scheduling, the NEH heuristic (Nawaz et al. 1983) is commonly regarded as the best constructive heuristic in the world to $\min(C_{max})$, based on which

heuristics are developed to improve utilization and to reduce CO_2 emission (Gahm et al. 2016, Fang et al. 2011, Ding et al. 2016). In contrast, the LR heuristic (Liu and Reeves 2001) and the FF heuristic (Fernandez-Viagas and Framinan 2015) are regarded as two of the best constructive heuristics to $\min(\sum C_j)$. However, two questions are left for operations management, given the inconsistency between $\min(C_{max})$ and $\min(\sum C_j)$ (Li et al. 2014). One question is whether near optimal solutions to simple objectives can balance the trade-offs (TO) between metrics based on C_{max} and metrics based on $\sum C_j$, and the other is whether the process is better under control if operations management focus on trade-off balancing instead on optimizing single objectives.

In this work, we develop and test a new heuristic that we name the current and future deviation (CFD) heuristic for sequencing/scheduling in a serial process with m machines or stages. The development of our CFD heuristic combines two underlying ideas. First, we use one set of weights to address two coupled deviations generated by one completion time from both upper and lower bounds as fundamental elements of the heuristic. Second, we employ another set of weights to balance trade-offs between results from two well-understood objectives: $\min(C_{max})$ and $\min(\sum C_j)$. Following the traditional notation in flow shop scheduling (T'kindt and Billaut 2002), we deal with a bi-criteria scheduling problem for an m-machine permutation ($prmu$) flow shop with a linear function (F_l) of two scheduling objectives of C_{max} and $\sum C_j$, $F|prmu|F_l(C_{max}, \sum C_j)$.

Two objectives of $\min(C_{max})$ and $\min(\sum C_j)$ are inconsistent with each other (Li et al. 2014), which means one completion time of a job j on a machine i, $C_{j,i}$, may minimize the deviation to one objective, but maximize the deviation to the other. Consequently in our CFD heuristic, we first factorize the two coupled deviations, and use weights α to construct an initial sequence. We then explicitly recognize the inconsistency between the results of $\min(C_{max})$ and $\min(\sum C_j)$, and use weights β in a linear trade-off function to reconstruct the initial sequence. Although both α and β are weights and can change separately, α is applied to fundamental elements of two coupled deviations at the operation level, and β is applied to performance at the process level. Through case studies in Section 4, preferences for trade-off balancing should be consistent at the both levels, which means $\alpha = \beta$.

Three separate datasets are used to test the performance of our CFD heuristic. The first dataset consists of randomly generated small-scale instances where optimal sequences can be found for $\min(C_{max})$, $\min(\sum C_j)$ and $\min(TO)$. The second dataset is classic Taillard's

benchmarks for flow shop scheduling (Taillard 1993). The third dataset consists historical records of nearly 30,000 patient cases from 2013-14 in OR scheduling across the three-stage periop process at University of Kentucky HealthCare (UKHC). Compared to NEH, LR and FF, we find that our CFD heuristic clearly outperforms all on $\min(C_{max})$, $\min(\sum C_j)$ and $\min(TO)$ for the dataset of small-scale instances, outperforms them for Taillard's benchmarks on $\min(C_{max})$ and $\min(TO)$, but marginally on $\min(\sum C_j)$ especially compared to FF, and dominates all for our UKHC dataset. In addition, using process control metrics we show that our CFD heuristic yields a process that is better under control than the historical data from UKHC. Finally, we compute Spearman rank order correlations among the sequences for $\min(C_{max})$, $\min(\sum C_j)$ and $\min(TO)$ for each dataset, finding that they are close to zero and empirically support the inconsistency between each pair of objectives.

Thus, our three main contributions are first developing a novel CFD heuristic that uses decoupled deviations from bounds and allows for trade-offs between objectives like $\min(C_{max})$ and $\min(\sum C_j)$, second showing that the CFD heuristic outperforms three leading alternative constructive heuristics based on a series of empirical tests across generated, benchmark, and real historical datasets, and third keeping serial processes better under control based on trade-off balancing.

The rest of this paper is organized as follows. A brief literature review is provided in Section 2, the programming logic and steps of our CFD heuristic are illustrated in Section 3, results of empirical case studies are analyzed in Section 4, and conclusion and future work are drawn in Section 5.

2. Literature Review

The literatures on production scheduling and on trade-off balancing (or multi-objective optimization) are vast. In this section, we provide brief reviews in these two areas from the perspective of heuristic development. For further details about prior research, refer to Pinedo (2008) and T'kindt and Billaut (2002) for flow shop scheduling, and to Malakooti (2013) and Slowinski and Weglarz (1989) for trade-off balancing.

2.1. Flow Shop Scheduling

Balancing trade-offs between $\min(C_{max})$ and $\min(\sum C_j)$ is still a fundamental challenge to scheduling in serial processes, especially with different objectives in operations management, and given Garey et al. (1976) proved that $\min(C_{max})$ is NP-complete for a flow

line with $m \geqslant 3$, and Hoogeveen and Kawaguchi (1999) proved that $\min(\sum C_j)$ is NP-complete for a flow line with $m \geqslant 2$. Research on flow shop scheduling has been carried out for more than 6 decades since the classic Johnson's algorithm in Johnson (1954). During the first two decades, research on flow shop scheduling focused on seeking optimal solutions by using optimization and branch & bound techniques (Gupta and Stafford 2006). However, the emergence of NP-completeness theory in the third decade (1975−1984) profoundly influenced the direction of research on flow shop scheduling, changing to seek near optimal solutions by using heuristics. Initially, $\min(C_{max})$ was the primary scheduling objective for permutation flow shop production. During the fourth decade (1985−1994), hybrid flow shop production emerged and many artificial intelligence (AI) based heuristics were developed. The fifth decade (1995−2004) witnessed the proliferation of various flow shop problems, objectives, and solution approaches. Current research on flow shop scheduling (2005−present) has extended to sustainability (Gahm et al. 2016) in terms of energy-efficiency, water usage, CO_2 emission (Ding et al. 2016, Fang et al. 2011, Zhang et al. 2014), which intensifies the necessity of trade-off balancing.

Framinan et al. (2004) proposed a general framework for heuristic development consisting of three phases: index development (generating an initial sequence), solution construction (changing the initial sequence based on some inserting schemes), and solution improvement (changing the job sequence based on AI). PDRs are typical examples in phase one. The NEH heuristic proposed by Nawaz, Enscore, and Ham (Nawaz et al. 1983) and the LR heuristic proposed by Liu and Reeves (2001) are typical examples in phase two that also spillover to phase three. As we indicated above, the NEH, LR and FF heuristics are the best of constructive heuristics to $\min(C_{max})$ and $\min(\sum C_j)$, respectively (Kalczynski and Kamburowski 2007, Ruiz and Maroto 2005, Fernandez-Viagas and Framinan 2015). Meta-heuristics, such as genetic algorithms, neural networks, and simulated annealing, are typical examples in phase three. Scheduling methods developed in the first two phases can facilitate heuristic development in phase three. In general, there is a trade-off between solution quality and computational complexity or computation time in choosing a heuristic for a scheduling problem. At one extreme, the solution quality of PDRs is low, but they provide a solution fast, saving time in decision making, and they are used in the other two phases of heuristic development. At the other extreme, the solution quality of meta-heuristics is

high, but it is time consuming to get a solution by using them (Ruiz and Maroto 2005). Our CFD heuristic proceeds through the first two phases of heuristic development above.

As we compare our CFD heuristic to the best of the best constructive heuristics in our empirical case studies, we briefly describe the key sequencing logics of the NEH, LR and FF heuristics. The LPT rule is used as an index function in the NEH heuristic to generate an initial sequence of n jobs. The first two jobs in the initial sequence are enumerated for a better partial solution to $\min(C_{max})$. As $j = 3, ..., n$ for each of the rest $n-2$ jobs in the initial sequence, job j is inserted into j possible positions in the intermediate sequence, and one of j partial sequences with $\min(C_{max})$ is selected for the next round of iteration until $j = n$. The computational complexity of the NEH heuristic originally was $O(n^3m)$, and was improved by Taillard (1990) to $O(n^2m)$ for n-job m-machine permutation flow shop problems to $\min(C_{max})$.

In the index development phase of the LR heuristic, an initial sequence is constructed based on an index function with the sum of two terms, weighted total idle times (IT) and artificial total flow times (AT). Afterwards, each of a number of x jobs is selected as the first job in the initial sequence and sequence reconstruction based on the above mentioned index function occurs, generating a number of x candidate LR(x) sequences, where $x = 1, ..., n$. Local search techniques of both forward pairwise exchanging (FPE) and backward pairwise exchanging (BPE) are then applied to x reconstructed sequences to improve the solution quality of LR(x) on $\min(\sum C_j)$. The computational complexity is $O(n^3m)$ for LR(1) without local search, and $O(n^4m)$ for LR(n) with local search. Based on Taillard's benchmarks (Taillard 1993), LR(n) outperformed six of other heuristics to $\min(\sum C_j)$ (Liu and Reeves 2001), including the Ho (1995) heuristic. Based on computational complexities in the same order, we compare our CFD heuristic to the NEH with the original settings and to the LR(1) without local search.

Similar to the LR heuristic, Fernandez-Viagas and Framinan (2015) also use AT and IT to construct a job sequence to $\min(\sum C_j)$. Their novel approach integrates two tuning parameters in the FF heuristic, specifically a parameter a in calculating AT' and another parameter b in calculating IT', by which the computational complexity of FF is reduced to $O(n^2m)$. After tuning the two parameters, the FF heuristic with $a = 4$ and $b = 1$ outperforms the LR heuristic on average for Taillard's benchmarks.

2.2. Trade-off Balancing

Without loss of generality, a multi-objective combinatorial optimization (MOCO) problem with a number of $q = 1, ..., O$ minimization objectives can be defined as follows (Czyzak and Jaszkiewics 1998), $\min\{z_1 = f_1(\mathbf{x}), z_2 = f_2(\mathbf{x}), ..., z_O = f_O(\mathbf{x})\}$, subject to $\mathbf{x} \in F$, where the solution $\mathbf{x}$ is a vector of discrete decision variables and F is the set of feasible solutions. Czyzak and Jaszkiewics (1998) explicitly pointed out two factors which cause difficulties in solving MOCO problems. The first is that intensive cooperation with decision makers (DMs) should be involved in seeking solutions, which requires efficient solutions generated by effective tools. The second is that an MOCO problem is more difficult to solve, if each problem of single-objective versions is NP-hard. "Priori" and "posteriori" approaches are widely used in seeking and evaluating solutions to MOCO problems, respectively (Ciavotta et al. 2013). A linear function with weights is a typical example of the "priori" approach, that is, $z = \sum_{q=1}^{O} \beta_q z_q$ with $\sum_{q=1}^{O} \beta_q = 1$. For example, Framinan et al. (2002) developed a bi-objective heuristic to minimize the weighted sum of C_{max} and $\sum C_j$, and the NEH insertion method was applied. In this heuristic, a function $TO = \beta \cdot \frac{n}{2} \cdot C_{max} + (1-\beta) \cdot \sum C_j$ was developed, where β is the weight on C_{max}, and an unscheduled job j with minimum TO is selected and attached to the current partial sequence. Pareto efficiency is a typical example of the "posteriori" approach. A solution $\mathbf{x} \in F$ is Pareto efficient, if and only if there is no $\mathbf{x}' \in F$ such that $\forall q \ f_q(\mathbf{x}') \leq f_q(\mathbf{x})$ and $\exists q \ f_q(\mathbf{x}') < f_q(\mathbf{x})$. Linear functions with weights as in the "priori" approach usually have metrics measured in different scales, and it is difficult to map β_q into valid preferences of DMs (Ciavotta et al. 2013).

Czyzak and Jaszkiewics (1998) proposed two quality metrics that respectively measure the average and maximum deviations between the set F and a reference set R, which can be used to address such a problem in the "priori" approach. Given $\mathbf{y} \in R$, the deviation defined in Czyzak and Jaszkiewics (1998) is $d_q(\mathbf{x}, \mathbf{y}) = \max\{0, [f_q(\mathbf{y}) - f_q(\mathbf{x})]/[f_q^{MAX}(R) - f_q^{MIN}(R)]\}$, where $f_q^{MAX}(R)$ and $f_q^{MIN}(R)$ are the maximum and minimum values of function f_q in the reference set R, respectively. Therefore, $[f_q(\mathbf{y}) - f_q(\mathbf{x})]/[f_q^{MAX}(R) - f_q^{MIN}(R)]$ is a normalized deviation. Based on normalized deviations of $d_q(\mathbf{x}, \mathbf{y})$, the first metric is defined as $D1_R = \frac{1}{|R|} \sum_{\mathbf{y} \in R} \min_{\mathbf{x} \in F}\{d_q(\mathbf{x}, \mathbf{y})\}$, where $|R|$ is the cardinality of set R. The second metric is defined as $D2_R = \max_{\mathbf{y} \in R}\{\min_{\mathbf{x} \in F}\{d_q(\mathbf{x}, \mathbf{y})\}\}$. $D1_R$ measures the average deviations with equal weights of $\frac{1}{|R|}$, and $D2_R$ measures the maximum deviation from the reference set. Moreover, Czyzak and Jaszkiewics (1998) pointed out that the lower the

ratio $D2_R/D1_R$, the more uniform the distribution of solutions from the set F over the set R. However, DMs should be cautious in using the ratio of $D2_R/D1_R$ to evaluate heuristics. A reason will be provided in Section 4.1 based on our case studies. Framinan (2009) and Ishibuchi et al. (2003) developed different metaheuristics by using the $D1_R$ metric, but with a slight modification, in which the deviation is measured by $d(\mathbf{x},\mathbf{y}) = \sqrt{\sum(f_q^*(\mathbf{y}) - f_q^*(\mathbf{x}))^2}$, and $f_q^*(\cdot) = [f_q(\cdot) - f_q^{MIN}(R)]/[f_q^{MAX}(R) - f_q^{MIN}(R)]$.

As we will see in the following sections, two underlying ideas characterize our CFD heuristic in trade-off balancing. Firstly, we operate on two coupled deviations and use α to decouple them at the operation level. Secondly, we use normalization not only on two coupled deviations at the operation level, but also on performances of C_{max} and $\sum C_j$ at the process level, and use β to address preferences on normalized performances. The magnitudes of C_{max} and $\sum C_j$ are not the same, which is the reason why Framinan (2009) used $\beta \cdot \frac{n}{2}$ to address this concern, but we use normalizations accordingly. Normalized C_{max} and $\sum C_j$ are dimensionless, and provide accurate values to our TO function for trade-off balancing. Consequently, our CFD heuristic outperforms the NEH and LR heuristics respectively on $\min(C_{max})$, $\min(\sum C_j)$, and $\min(TO)$, whereas Framinan et al.'s heuristic outperforms other heuristics in their case studies only on $\min(TO)$, but does not outperform the NEH heuristic on $\min(C_{max})$, nor the Ho (1995) heuristic on $\min(\sum C_j)$.

Trade-offs should be balanced not only at the system level, but also at the process and operation levels. We note that decision making on trade-off balancing only at the system level is not effective. For example, the economic order quantity (EOQ) model proposed by Harris in 1913, reprinted in Harris 1990, has been widely applied to balance trade-offs between production cost and holding cost at the system level. Based on the EOQ model, many other models have been developed for ordering in different situations, such as the newsvendor model (Stevenson 2009) and (Q,r) model (Hopp and Spearman 2000). These trade-off-based models are often embedded in software developed for manufacturing and services, such as ERP and MRP-II systems (Hopp and Spearman 2000, Orlicky 1975). As a result, WIP inventory levels are still high in manufacturing systems (GeneralElectric 2014), and waiting times for a surgery are still long in healthcare systems (AHRQ 2013). In our CFD heuristic, weights α balance trade-offs at the operation level for each job on each machine, and weights β balance trade-offs at the process level for the performance of a whole serial process.

3. A Current and Future Deviations Heuristic

In this section, we first address the concept of deviation from bounds (DB) at the operation level, which are the reference values of lower and upper bounds of completion times, denoted as $OLC_{j,i}$ and $OUC_{j,i}$, and by using which we model the two coupled deviations and develop an index function with α to generate an initial sequence in phase one of index development. Second, we address the lower and upper bounds of completion times at the process level, denoted as $PLC_{j,i}$ and $PUC_{j,i}$, deviations from which are used in phase two of solution construction. Third, we address how we model trade-offs at the process level by using β to reconstruct the initial sequence to obtain a final sequence.

3.1. Two Coupled Deviations for Trade-offs as Initial Sequence

Let $p_{j,i}$ denote the processing time of job j on machine i. For a given sequence, we can calculate completion times by $C_{j,i} = \max\{C_{j,i-1}, C_{j-1,i}\} + p_{j,i}$, where $C_{j,i}$ is the completion time of the current job j in the sequence on current machine i, $C_{j,i-1}$ is the completion time of job j on previous machine $i-1$, and $C_{j-1,i}$ is the completion time of previous job $j-1$ in the sequence on current machine i (Pinedo 2008). Based on a state space (SS) concept proposed by Li et al. (2011b) for flow shop scheduling, a time buffer can be defined as $B_{j,i} = C_{j,i} - C_{j,i-1}$, which is actually for the next job $j+1$ to be processed on the previous machine $i-1$ without causing an idle time $I_{j+1,i} = \max\{C_{j+1,i-1} - C_{j,i}, 0\}$ on current machine i. Although a large time buffer $B_{j,i}$ may reduce the sum of idle times and be good to $\min(C_{max})$, it can enlarge the completion time, $C_{j,i}$, and be not good to $\min(\sum C_j)$. For an m-machine flow line, there can be $m-1$ time buffers between each pair of machines, which are created by job j. Thus, one completion time $C_{j,i}$ contributes to $\min(C_{max})$ and $\min(\sum C_j)$ differently.

Given a partial sequence S for scheduled jobs, we need to calculate completion times for any unscheduled job $j \in U$, which is attached to S, and approximate completion times for the rest of $|U|-1$ jobs. The programming logic is as follows. Given a vector of $1 \times m$ completion times for the last job $h \in S$, we can attach any job $j \in U$ to S, and calculate it's completion times of $[C_{j,i}]_{1\times m}$. Initially, $S = \emptyset$, $|U| = n$, and $C_{h,i} = [0]_{1\times m}$. To save computation time for completion time approximation of the rest of $|U|-1$ jobs, we can use average processing times (APT) to calculate artificial completion times ($AC_{k,i}$) for $k \in U \backslash j$, where $APT_i = \sum_{k\in U\backslash j} p_{k,i}/(|U|-1)$ (Li et al. 2011a). Consequently, we can have

a three-dimensional matrix of $\left[C^U_{j,i}\right]_{|U|\times m\times|U|}$, where each element in the third dimension represents a $|U|\times m$ matrix of completion times by attaching a job $j\in U$ to S. Based on the third dimension of $\left[C^U_{j,i}\right]$, the reference values for lower and upper bounds of completion times at the operation level for each job j on each machine i are calculated as,

$$\begin{aligned} OLC_{j,i} &= \min_{j\in U}\{C^U_{j,i}\} \text{ for } i=1,...,m,\\ OUC_{j,i} &= \max_{j\in U}\{C^U_{j,i}\} \text{ for } i=1,...,m. \end{aligned} \tag{1}$$

Given $\left[C^U_{j,i}\right]$, $OLC_{j,i}$ and $OUC_{j,i}$ for $j\in U$, we can quantify two coupled deviations, as shown in Figure 1. In the next subsection, we provide a programming logic to calculate lower and upper bounds at the process level, $PLC_{j,i}$ and $PUC_{j,i}$.

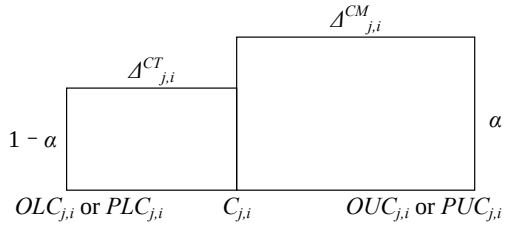


Figure 1 Two coupled deviations

As a completion time $C_{j,i}$ approaches the upper bound of $OUC_{j,i}$, it is good to minimize maximum completion time ($\min(C_{max})$) from the idle time perspective, and as $C_{j,i}$ approaches the lower bound of $OLC_{j,i}$, it is good to minimize total completion time ($\min(\sum C_j)$) from the completion time perspective. These two coupled deviations for $\min(C_{max})$ and $\min(\sum C_j)$, represented by superscripts CM and CT, respectively, are defined as

$$\begin{aligned} \Delta^{CM}_{j,i} &= OUC_{j,i} - C_{j,i},\\ \Delta^{CT}_{j,i} &= C_{j,i} - OLC_{j,i}. \end{aligned}$$

The aggregation of these two coupled deviations are defined as

$$\begin{aligned} \Sigma^{CM}_j &= \sum_{i=1}^{m} \Delta^{CM}_{j,i} \text{ for } j\in U,\\ \Sigma^{CT}_j &= \sum_{i=1}^{m}\sum_{j=1}^{|U|} \Delta^{CT}_{j,i} \text{ for } j\in U, \end{aligned}$$

where the effect of $\Delta_{j,i}^{CM}$ only for current job $j \in U$ on all m machines is taken into consideration in Σ_j^{CM}, but the effect of $\Delta_{j,i}^{CT}$ for all jobs in U and on all m machines is taken into consideration in Σ_j^{CT}. Given a number of $|U|$ aggregations of Σ_j^{CM} and Σ_j^{CT}, we can calculate the variation ranges of Σ_j^{CM} and Σ_j^{CT}, respectively, by

$$R_j^{CM} = \max_{j \in U}\{\Sigma_j^{CM}\} - \min_{j \in U}\{\Sigma_j^{CM}\},$$
$$R_j^{CT} = \max_{j \in U}\{\Sigma_j^{CT}\} - \min_{j \in U}\{\Sigma_j^{CT}\}.$$

Such variation ranges are fixed for evaluating current unscheduled jobs in U.

Our index function to generate the initial sequence is defined as

$$\min_{j \in U}\{\alpha \cdot \frac{\Sigma_j^{CM}}{R_j^{CM}} + (1-\alpha) \cdot \frac{\Sigma_j^{CT}}{R_j^{CT}}\}. \tag{2}$$

Different from the Framinan et al. (2002) heuristic that directly operates on completion times, we operate on normalized deviations of Σ_j^{CM} and Σ_j^{CT} from $OUC_{j,i}$ and $OLC_{j,i}$. The aggregations of two coupled deviations have different impacts on $\min(C_{max})$ or $\min(\sum C_j)$, even though they are normalized. Assigning a weighting factor $\alpha = 0.0 : 0.1 : 1.0$ on Σ_j^{CM} to $\min(C_{max})$ and $(1-\alpha)$ on Σ_j^{CT} to $\min(\sum C_j)$, we can choose a job $j \in U$ with the minimum sum of weighted deviations, and attach it to S for sequenced jobs. Thus, α serves as a weight for the $\min(C_{max})$ objective relative to the $\min(\sum C_j)$ objective.

Given an initial sequence based on deviations from bounds at the operation level, we reconstruct the sequence based on the bounds at the process level. Next we provide details in calculating $PLC_{j,i}$ and $PUC_{j,i}$.

3.2. Lower and Upper Bounds at the Process Level

Given a completion time of job j on each machine i that $C_{j,i} = \max\{C_{j,i-1}, C_{j-1,i}\} + p_{j,i}$ (Pinedo 2008), where $p_{j,i}$ is the processing time, an idle time can be calculated by $I_{j,i} = \max\{C_{j,i-1} - C_{j-1,i}, 0\}$. Minimum idle times on machine i are generated when completion times on machine $i-1$ are small, but those on machine i are large, which means jobs are leaving machine $i-1$ and arriving at machine i quickly, but leaving machine i slowly. In contrast, jobs leaving machine $i-1$ slowly and leaving machine i quickly generate maximum idle times. Therefore, minimum and maximum idle times, $I_{j,i}^{MIN}$ and $I_{j,i}^{MAX}$, are two key elements in calculating lower and upper bounds of completion times at the process level, $PLC_{j,i}$ and $PUC_{j,i}$, for each job j on each machine i.

Processing times $p_{j,i}$ on each machine $i = 1, ..., m$ can be sorted into two series. One series of processing times is sorted by the LPT rule in a non-ascending order, recorded as $p_{j,i}^{LPT}$, and the other is sorted by the SPT rule in a non-descending order, recorded as $p_{j,i}^{SPT}$. Given the assumptions that all of n jobs are available to be processed on machine 1 at time zero, which means there is no idle times on machine 1 so $I_{j,1}^{MIN} = 0$ and $I_{j,1}^{MAX} = 0$, we calculate $PLC_{j,i}$ and $PUC_{j,i}$ as follows:

$$\begin{aligned} I_{j,i}^{MIN} &= \max\{PLC_{j,i-1} - PUC_{j-1,i}, 0\} \\ &= \max\{(PLC_{j-1,i-1} + I_{j,i-1}^{MIN} + p_{j,i-1}^{SPT}) - (PUC_{j-2,i} + I_{j-1,i}^{MAX} + p_{j-1,i}^{LPT}), 0\}, \end{aligned} \tag{3}$$

$$\begin{aligned} I_{j,i}^{MAX} &= \max\{PUC_{j,i-1} - PLC_{j-1,i}, 0\} \\ &= \max\{(PUC_{j-1,i-1} + I_{j,i-1}^{MAX} + p_{j,i-1}^{LPT}) - (PLC_{j-2,i} + I_{j-1,i}^{MIN} + p_{j-1,i}^{SPT}), 0\}, \end{aligned} \tag{4}$$

and thus

$$PLC_{j,i} = PLC_{j-1,i} + I_{j,i}^{MIN} + p_{j,i}^{SPT} \text{ and } PUC_{j,i} = PUC_{j-1,i} + I_{j,i}^{MAX} + p_{j,i}^{LPT}. \tag{5}$$

3.3. An Evaluation Function for Trade-offs in Sequence Reconstruction

After generating an initial sequence based on (2), we reconstruct the sequence based on the following scheme to address trade-offs between output variables at a production line or process level. Our trade-off function to finalize a sequence is defined as

$$\min_{r=1,...,j} \{\beta \cdot \frac{C_{j,m} - PLC_{1,m}}{PUC_{j,m} - PLC_{1,m}} + (1-\beta) \cdot \frac{\sum_{k=1}^{j}(C_{k,m} - PLC_{k,m})}{\sum_{k=1}^{j}(PUC_{k,m} - PLC_{k,m})}\}, \tag{6}$$

where r represents a possible position of job j in the partial sequence of $S \cup \{j\}$, and $\beta = 0.0 : 0.1 : 1.0$ represents a preference for $\min(C_{max})$ relative to $\min(\sum C_j)$. The optimization in (6) evaluates output deviations on the last machine m and from the lower bounds of PLC for both $\min(C_{max})$ and $\min(\sum C_j)$. Different from calculation at the operation level, the deviation for $\min(C_{max})$ on machine m is based on the difference between the completion time for current job j and the lower bound for job 1, and the deviation for $\min(\sum C_j)$ is only for current j jobs in S. This scheme can be extended to evaluate output deviations on any machine or stage, depending on management concerns.

Similar to the NEH heuristic, we enumerate the first two jobs in the initial sequence, and get a partial sequence S with a better value in (6). As $j = 3, ..., n$ for the remaining jobs, we put job j into $r = 1, ..., j$ possible positions of the partial sequence S, and based on the minimum value of (6), we can finalize a sequence for trade-off balancing.

The computational complexity of this sequence reconstruction is $O(n^3m)$. Therefore, the overall computational complexity of CFD is $O(n^3m)$. Allowing for the weights given to $\min(C_{max})$ and $\min(\sum C_j)$ to differ in the generation of an initial sequence (α) and in the sequence reconstruction (β) provides additional flexibility in trade-off balancing in our CFD heuristic.

3.4. Programming Logic and Pseudocode

The programming logic and steps of our CFD heuristic are summarized as follows.

Step 0. Initialization, $[P]_{n\times m}$ for processing times, S for scheduled jobs, which can be empty initially, U for unscheduled jobs, which can be $\{1,...,n\}$ initially, lower and upper bounds of completion times at the process level, $PLC_{j,i}$ and $PUC_{j,i}$, which are sequence independent, according to (3), (4), and (5).

Step 1. Generation of an initial sequence according to (1) and (2). A pseudocode is provided in Figure 2.

Step 2. Reconstruction of the initial sequence based on (6) and by using the insertion scheme as in the NEH heuristic, for details of which please refer to Section 2.1 or Nawaz et al. (1983).

```
function [S, Cmax, ∑C] = CFD_InitialSeq (P, α, PLC, PUC)
  Sum_P = sum(P,1);                 %this is for the sum of processing times on each machine
  C_h = zeros(1,m);                 %for completion time of the last job h in S, initially it is a vector of zeros
  S = [];                           %for scheduled jobs, initially it is empty
  U = [1:n];                        %for unscheduled jobs, initially it equals to all jobs
  for h = 1:n-1
      Calculate [C^U_{j,i}]_{|U|×m×|U|};   %according to current completion times of C_h
      Calculate OLC_{j,i} and OUC_{j,i};   %based on Eq. (1)
      Calculate Δ^CM_{j,i} and Δ^CT_{j,i};  %for two coupled deviations
      Calculate Σ^CM_j and Σ^CT_j;          %for the aggregation of two coupled deviations
      Calculate R^CM_j and R^CT_j;          %for normalization
      Update S, U, and C_h;                 %based on Eq. (2)
  end
  Attach the only one job left in U into S;
  Calculate Cmax, ∑C;
  Return S, Cmax, ∑C;
end of CFD_InitialSeq()
```

Figure 2 Pseudocode for an initial sequence

4. Case Studies

To verify the effectiveness of our CFD heuristic in balancing trade-offs between $\min(C_{max})$ and $\min(\sum C_j)$ by using two coupled deviations, we carry out case studies on three types

of data: small-scale instances, Taillard's benchmarks, and historical OR data from the University of Kentucky HealthCare (UKHC). We present the results respectively for each type of data, and then we discuss the empirical relationships among different sequences to $\min(C_{max})$, $\min(\sum C_j)$ and $\min(TO)$ which we define in (9) below, generated by our CFD heuristic using different weights.

4.1. 5400 Small-Scale Instances

For small-scale instances, the number of jobs ranges from $n = 5, ..., 10$, yielding six options, and the number of machines is set at $m = 2 \cdot (i + 1)$ for $i = 1, ..., 9$, yielding nine options ranging from 5 to 20. For each of the resulting 54 combinations, 100 instances are randomly generated, and the processing times follow a uniform distribution between $[1, 99]$. Therefore, there are 5400 small-scale instances in total.

Because the number of jobs is relatively small, $n \leq 10$, we can use an enumeration method to find the best (or minimum) and worst (or maximum) solutions to $\min(C_{max})$ and $\min(\sum C_j)$ as references R. Given best and worst values of $f_{q,k}^{MIN}$ and $f_{q,k}^{MAX}$ for each instance k and for each objective q, with $q = 1$ for $\min(C_{max})$ and $q = 2$ for $\min(\sum C_j)$, we can define a normalized deviation (ND) as follows,

$$ND_{q,k}(H, R) = \frac{f_{q,k}(H) - f_{q,k}^{MIN}(R)}{f_{q,k}^{MAX}(R) - f_{q,k}^{MIN}(R)} \cdot 100, \tag{7}$$

where $f_{q,k}(H)$ is the solution generated by a scheduling method H. This $ND_{q,k}(H, R)$ is normalized in the same way as $d_q(\mathbf{x}, \mathbf{y})$ defined in Czyzak and Jaszkiewics (1998). Similarly, Fernandez-Viagas and Framinan (2015) defined a relative percentage deviation (RPD) as $RPD_{q,k}(H, R) = [f_{q,k}(H) - f_{q,k}^{MIN}(R)]/f_{q,k}^{MIN}(R) \cdot 100$. Accordingly, an average normalized deviation (AND) is defined as follows,

$$AND_q(H, R) = \frac{1}{K} \sum_{k=1}^{K} ND_{q,k}(H, R), \tag{8}$$

where K is the number of instances.

Based on AND_q for each objective, our trade-off function is defined as follows,

$$TO(H, R) = \beta \cdot AND_1(H, R) + (1 - \beta) \cdot AND_2(H, R). \tag{9}$$

This evaluation metric for trade-off balancing is similar to but different from the $D1_R$ metric defined in the literature. First, $TO(H, R)$ flexibly integrates DMs' preferences into

the evaluation, by changing weights β on $\min(C_{max})$, not by equal weights as defined in Czyzak and Jaszkiewics (1998). Second, $TO(H,R)$ actually is the expected value of trade-off balancing, not a standard deviation, as a squared root of the sum of squared differences defined in Ishibuchi et al. (2003).

Given $\alpha=\beta$ in (2) and (6), our CFD(α) heuristic generates 11 sequences, each of which has $[AND_1, AND_2]$ values. The comparison between the CFD(α), NEH, LR, and FF heuristics is shown in Table 1 based on TO values defined in (9) for all 5400 small-scale instances, where the FF heuristic has parameters $a=4$ and $b=1$.

Table 1 Balancing Trade-offs between $\min(C_{max})$ and $\min(\sum C_j)$ for Small-Scale Instances

$\beta \setminus \alpha$	CFD(α)											NEH	LR(1)	FF
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0			
0.0	**14.71**	15.60	20.28	26.56	35.14	44.33	52.34	59.67	66.50	73.40	82.88	82.52	23.04	28.79
0.1	20.62	**20.03**	23.03	27.74	34.65	42.21	48.85	55.10	61.05	67.15	75.62	75.29	28.25	35.08
0.2	26.54	**24.45**	25.79	28.92	34.16	40.09	45.35	50.53	55.61	60.89	68.35	68.07	33.46	41.37
0.3	32.46	28.88	**28.55**	30.11	33.66	37.96	41.85	45.96	50.16	54.63	61.09	60.85	38.66	47.66
0.4	38.37	33.31	31.31	**31.29**	33.17	35.84	38.35	41.39	44.71	48.38	53.83	53.63	43.87	53.95
0.5	44.29	37.73	34.06	**32.47**	32.67	33.72	34.85	36.82	39.27	42.12	46.57	46.41	49.07	60.24
0.6	50.21	42.16	36.82	33.65	32.18	31.60	**31.35**	32.25	33.82	35.86	39.30	39.19	54.28	66.53
0.7	56.12	46.58	39.58	34.84	31.69	29.48	27.86	**27.68**	28.37	29.61	32.04	31.97	59.48	72.82
0.8	62.04	51.01	42.33	36.02	31.19	27.35	24.36	23.11	**22.92**	23.35	24.78	24.75	64.69	79.11
0.9	67.96	55.43	45.09	37.20	30.70	25.23	20.86	18.55	17.48	**17.10**	17.51	17.53	69.90	85.40
1.0	73.87	59.86	47.85	38.38	30.20	23.11	17.36	13.98	12.03	10.84	**10.25**	10.30	75.10	91.69
Avg.	44.29	37.73	34.06	**32.47**	32.67	33.72	34.85	36.82	39.27	42.12	46.57	46.41	49.07	60.24
StD	19.62	14.68	9.14	3.92	**1.64**	7.04	11.60	15.16	18.07	20.75	24.09	23.95	17.27	20.86
Two-tailed *t*-test against the best method														
C_{max}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	0.74	0.00	0.00
$\sum C_j$	--	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TO	0.10	0.33	0.68	0.91	--	0.54	0.48	0.33	0.21	0.13	0.07	0.07	0.02	0.00

Recalling that α is the weight for the initial sequence and β is the weight for the sequence reconstruction, for $\alpha=0.0$ and $\beta=0.0$ the entry in Table 1 represents the average of absolute deviations weighted to the $\min(\sum C_j)$ objective, for which CFD(0.0) achieves the smallest AND_2 of 14.71, the LR and FF achieve deviations of 23.04 and 28.79, respectively. Further, when $\alpha=1.0$ and $\beta=1.0$ the entry in Table 1 represents the average normalized deviations weighted to the $\min(C_{max})$ objective, for which CFD(1.0) achieves the smallest AND_1 of 10.25, and the NEH achieves a deviation of 10.30. Given different levels of preferences for $\min(C_{max})$ relative to $\min(\sum C_j)$ such that $\beta=0.0:0.1:1.0$, CFD(0.3) achieves the smallest average (Avg) TO value of 32.47, and CFD(0.4) achieves the smallest

standard deviation (StD) of 1.64. Notice that the LR heuristic generates smaller deviations than the FF heuristic for all different levels of preferences β for small-scale instances.

For each of three objectives, a two-tailed t-test is carried out among the 14 sequencing methods (NEH, LR, FF and 11 of CFD) against the best one on $\min(C_{max})$, $\min(\sum C_j)$ and $\min(TO)$ respectively, and the p-value is provided in Table 1. Given a 95% confidence interval, we can tell from Table 1 that CFD(1.0) is not significantly different from the NEH heuristic on $\min(C_{max})$, although it achieves a smaller AND_1 value on $\min(C_{max})$. CFD(0.0,0.1,0.2) heuristics are significantly different from the LR and FF heuristics and achieve better average values on $\min(\sum C_j)$ for small-scale instances. CFD(0.3) and CFD(0.5) are not significantly different from each other on $\min(TO)$, but significantly different from the LR and FF heuristics.

To better understand the ratio of maximum deviation to average deviation, similar to $D2_R/D1_R$ from Czyzak and Jaszkiewics (1998), we provide maximum (Max), minimum (Min), and standard deviation (StD) of TO values in Table 2, in which, setting preferences for $\beta = 0.0$ or 1.0, trade-off value TO reduces to average normalized deviation for $\min(\sum C_j)$ or for $\min(C_{max})$, respectively.

Table 2 **Average Normalized Deviation (AND) on $\min(C_{max})$ and $\min(\sum C_j)$ for Small-Scale Instances**

$\beta \setminus \alpha$		CFD(α)											NEH	LR(1)	FF
		0.0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**			
	Avg	**14.71**	15.60	20.28	26.56	35.14	44.33	52.34	59.67	66.50	73.40	82.88	82.52	23.04	28.79
(0.0)	Max	100	100	100	100	100	100	100	100	100	100	100	100	100	100
$\sum C_j$	Min	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	StD	**0.20**	0.21	0.23	0.26	0.29	0.31	0.32	0.32	0.31	0.30	0.26	0.26	0.26	0.30
	Max/Avg	6.80	6.41	4.93	3.77	2.85	2.26	1.91	1.68	1.50	1.36	**1.207**	1.212	4.34	3.47
	Avg	73.87	59.86	47.85	38.38	30.20	23.11	17.36	13.98	12.03	10.84	**10.25**	10.30	75.10	91.69
(1.0)	Max	100	100	100	100	100	100	100	100	100	100	100	100	100	100
C_{max}	Min	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	StD	0.29	0.32	0.32	0.29	0.26	0.23	0.21	0.18	0.17	0.16	**0.153**	0.154	0.30	0.19
	Max/Avg	1.35	1.67	2.09	2.61	3.31	4.33	5.76	7.16	8.31	9.23	9.75	9.70	1.33	**1.09**

From Table 2, we can see that the maximum and minimum deviations are 100% and 0% respectively, for all heuristics among 5400 small-scale instances. Although CFD(0.0) achieves the smallest average and standard deviation values for $\min(\sum C_j)$ respectively, CFD(1.0) has the smallest ratio of Max/Avg, which is 1.19. Similarly, CFD(1.0) achieves the smallest Avg and StD values for $\min(C_{max})$ respectively, but FF has the smallest

ratio of Max/Avg, which is 1.09. This result clearly shows that the distribution of performance is more complex than can be evaluated simply by a ratio, and more statistically robust methods such as statistical process control (SPC) techniques we use in the following sections can be more reliable.

These results for small-scale instances, based on deviations from optimal solutions, answer the first question of whether near optimal solutions to simple objectives can balance the trade-offs. Based on a 2-tuple of $[AND_1(H,R), AND_2(H,R)]$ that represent deviations from optimal solutions for a given method q across $\min(C_{max})$ and $\min(\sum C_j)$, $[10.25, 82.88]$ for CFD(1.0) has a small deviation on $\min(C_{max})$ but a large deviation on $\min(\sum C_j)$, and $[73.87, 14.71]$ for CFD(0.0) has a large deviation on $\min(C_{max})$ but a small deviation on $\min(\sum C_j)$. Comparatively, $[23.11, 44.33]$ for CFD(0.5) is between those deviations for CFD(1.0) and CFD(0.0), respectively. The trade-off values against β are plotted in Figure 3 below, from which we can see that CFD(0.0,0.5,1.0) dominates the NEH and LR heuristics for any preferences over values of β on $\min(C_{max})$, and CFD(0.5) has the smallest trade-off values when β changes approximately from 0.4 to 0.7. Therefore, we conclude that near optimal solutions to simple objectives cannot balance the trade-offs between multiple objectives, given the inconsistency between objectives and different preferences across multiple objectives.

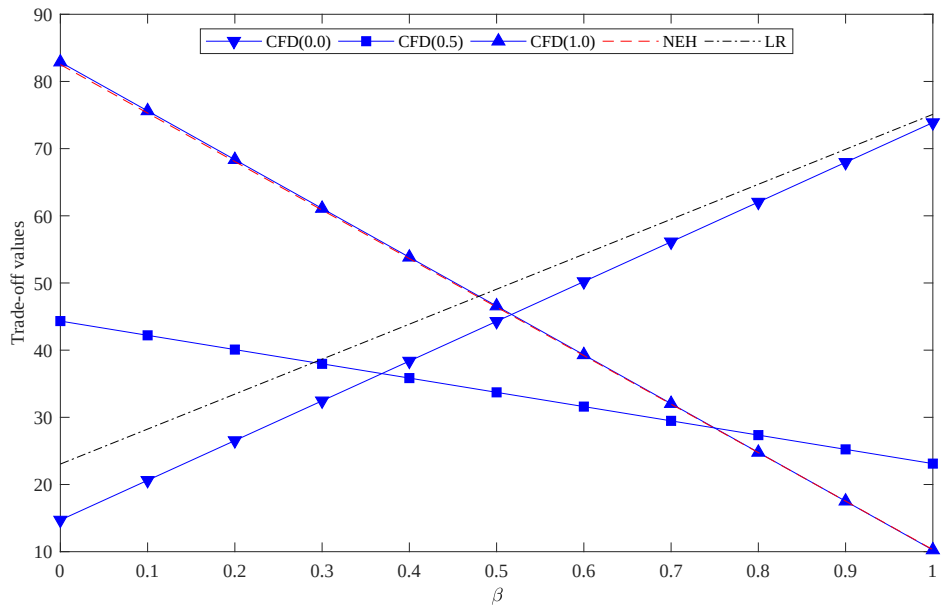


Figure 3 **Trade-off Values vs. Preferences Over β on $\min(C_{max})$**

4.2. 120 Instances in Taillard's Benchmarks

Taillard's benchmarks are classic in flow shop scheduling, and are commonly used to test scheduling methods on $\min(C_{max})$ and on $\min(\sum C_j)$. There are 12 scales in Taillard's benchmarks, ranging from a 20-job 5-machine flow line to a 500-job 20-machine flow line, 10 instances in each scale, and 120 instances in total.

Because $\min(C_{max})$ and $\min(\sum C_j)$ are NP-complete problems, best known solutions (B) are used to calculate normalized deviations, instead of using optimal solutions. B_1 for $\min(C_{max})$ can be found at `http://mistic.heig-vd.ch/taillard/`. B_2 for $\min(\sum C_j)$ is the minimum between the FF results and those in Liu and Reeves (2001), in which scheduling methods with high computational complexities are involved in generating B_2, such as meta-heuristics and LR(n) with FPE(n) and BPE(n). As maximization is involved in this type of case studies on Taillard's benchmarks, normalized deviations from best solutions are calculated as follows,

$$ND_{q,k} = \frac{|f_{q,k}(H,R) - B_{q,k}(R)|}{|W_{q,k}(R) - B_{q,k}(R)|} \cdot 100,$$

where $W_{q,k}(R)$ represents the worst solution for an instance k. If minimization is an objective, then $B_q = \min_R f_q(R)$ and $W_q = \max_R f_q(R)$. Contrarily, if maximization is an objective, then $B_q = \max_R f_q(R)$ and $W_o = \min_R f_q(R)$.

To compare our CFD heuristic with NEH, LR and FF, we calculate four other performance measures in addition to $\min(C_{max})$ and $\min(\sum C_j)$. The first is the average utilization ($Util$) of a flow line, which relates to workload, $\sum p_j$, and maximum completion time C_{max} on each machine. The second is the average WIP inventory level ($WIP\text{-}A$), which relates to $\sum C_j$ on each machine. The third is the sum of maximum WIP inventory levels ($WIP\text{-}MS$), which means the overall holding capacity of $m-1$ WIP inventories in a flow line. The fourth is the maximum of max WIP inventory capacity ($WIP\text{-}MM$) that indicates the maximum of $m-1$ WIP inventories, the location of which is meaningful for operations management. Li and Freiheit (2016) provide details for calculating these performance measures. The best and worst solutions on these four performance measures are based on actual performance of the NEH, LR, and CFD(α) heuristics. The average normalized deviations on each objective are provided in Table 3, for all 120 instances and for the NEH, LR, FF, CFD(α) heuristics.

Table 3 **Average Normalized Deviations by CFD(α), NEH, LR and FF Heuristics for Taillard's Benchmarks**

Metrics	CFD(α)											NEH	LR(1)	FF
	0.0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**			
C_{max}	86.93	55.71	46.86	40.96	35.58	27.20	22.94	**21.12**	21.22	21.33	21.96	22.04	84.99	87.91
$\sum C_j$	20.78	22.11	25.16	31.43	40.60	59.42	68.83	75.83	78.64	85.17	86.77	87.90	22.59	**19.88**
Util	83.60	63.98	53.21	48.64	38.41	22.95	15.83	12.70	13.88	**11.89**	15.11	14.42	86.28	82.69
WIP-A	**10.41**	18.38	23.53	32.03	41.93	53.21	64.08	68.78	70.90	76.80	85.98	88.45	11.38	12.01
WIP-MS	**6.95**	11.45	13.52	17.82	23.04	26.07	30.33	31.48	32.94	36.58	43.27	45.24	15.65	6.96
WIP-MM	29.50	28.42	**27.25**	29.86	33.72	28.86	32.34	34.27	33.80	35.41	40.27	41.94	36.99	27.26
Two-tailed *t*-test against the best method														
C_{max}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	0.88	0.77	0.20	0.20	0.00	0.00
$\sum C_j$	0.56	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	--
Util	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.58	0.14	--	0.05	0.11	0.00	0.00
WIP-A	--	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.32
WIP-MS	--	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WIP-MM	0.46	0.68	--	0.32	0.05	0.63	0.09	0.04	0.06	0.01	0.00	0.00	0.01	0.01

In Table 3, average normalized deviations are evaluated from the best solutions. Therefore, the smaller the value, the better the solution, and the minimum average deviations are in bold for each performance measure. The p-values of two-tailed t-tests are also provided in Table 3 against the best sequencing method.

For min(C_{max}), CFD(0.7) has the lowest AND value of 21.12, but based on the t-test, it is not significantly different from those of CFD(0.8,0.9,1.0) and NEH on a 95% confidence interval. In this sense, their performances are equivalent on min(C_{max}), although each of CFD(0.7,0.8,0.9,1.0) methods has an AND value smaller than that of 22.04 for NEH.

For min($\sum C_j$), FF has the lowest AND value of 19.88, followed by that of 20.78, 22.11 and 22.59 for CFD(0.0), CFD(0.1) and LR heuristics respectively. Based on the t-tests, neither CFD(0.0), CFD(0.1) or LR is significantly different from FF. However, both CFD(0.0) and CFD(0.1) achieve the negative values of $ND_{q,k}(H,R)$ for Taillard's benchmarks, which indicate that the CFD(0.0) and CFD(0.1) methods generate solutions better than those generated by FF and in Liu and Reeves (2001) on two instances by CFD(0.0) and on one instance by CFD(0.1).

For max($Util$), each of CFD(0.7,0.8,0.9) methods outperforms NEH on average, with the smallest AND value of 11.89 by CFD(0.9), but based on the t-tests, the four methods of NEH and CFD(0.7,0.8,0.9) are not significantly different in maximizing utilization.

For min(WIP-A), CFD(0.0) requires the lowest WIP inventory capacities on average, but based on the t-test, the LR and FF heuristics do not have a significantly different performance. However, for min(WIP-MS), it is still CFD(0.0) that requires the lowest overall

WIP inventory capacities across the process, but based on the t-test, it is significantly lower than other heuristics.

Finally, for min(WIP-MM), CFD(0.2) requires the lowest maximum WIP inventory capacity, and based on the t-test, CFD(0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.8) are not significantly different from each other.

Using the "posteriori" approach, we generate a Pareto frontier in Figure 4 based on AND values generated by CFD(α), NEH, LR and FF heuristics, from which we can clearly see that CFD(0.7) dominates CFD(0.8,0.9,1.0) and NEH heuristics.

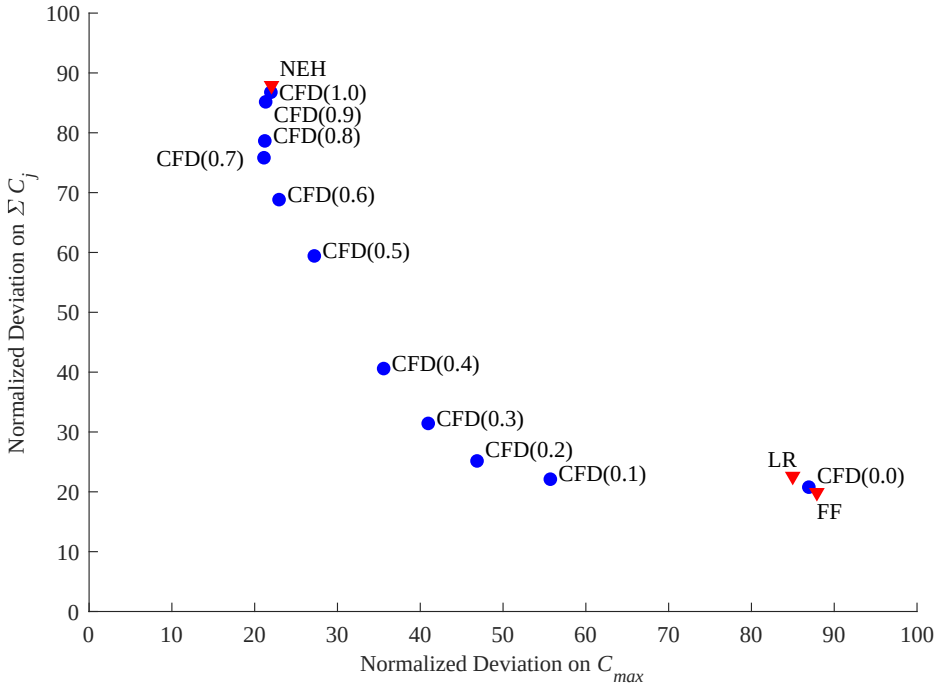


Figure 4 A Pareto Frontier Based on Average Normalized Deviations on C_{max} and on $\sum C_j$

To answer the second question, whether the process is better under control if operations management focuses on balancing trade-offs instead on optimizing single objectives, we generate control charts from the statistical process control (SPC) perspective, and show X-bar and R charts in Table 4, the values of which are based on AND generated by CFD(1.0), CFD(0.0), and CFD(0.5) methods for min(C_{max}), min($\sum C_j$), and min(TO), respectively. The average performance in X-bar charts, the average variation ranges in R charts, and relative upper and lower control limits (UCL and LCL) for X-bar and R are summarized in Table 5. For details of SPC techniques, refer to Montgomery (2007).

Table 4 Control Charts for Trade-off Balancing on Taillard's Benchmarks

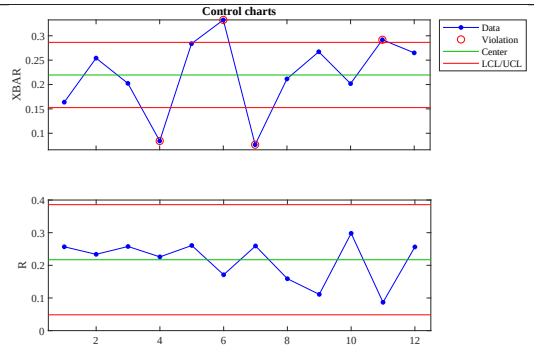
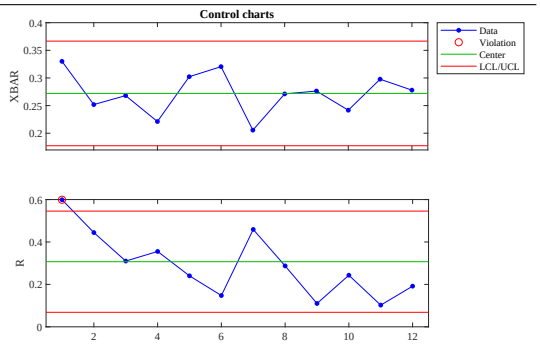
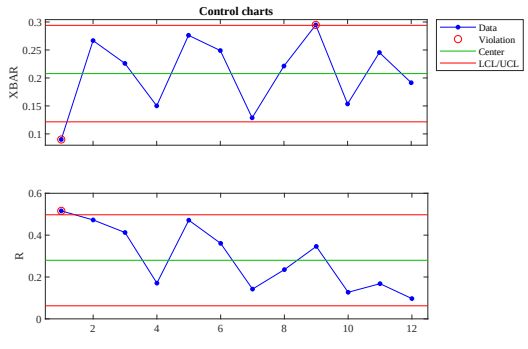
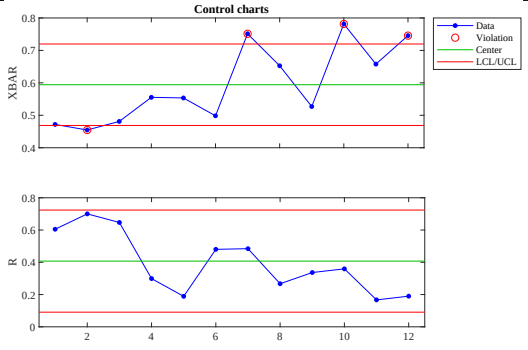
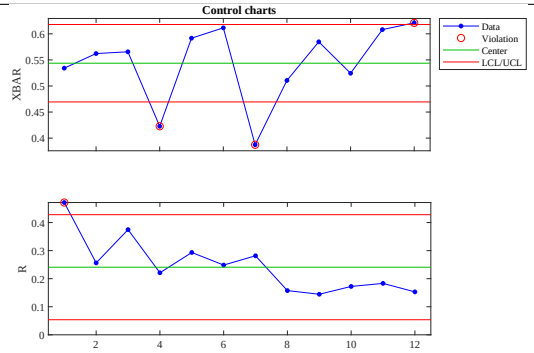
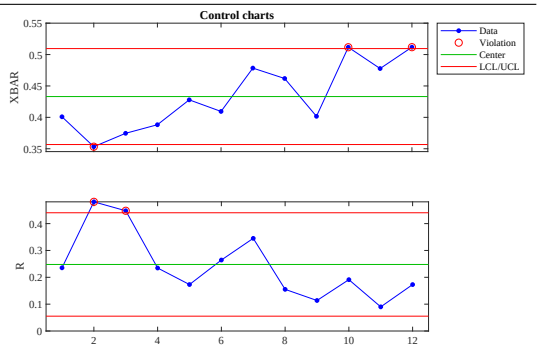
$o\backslash h$	CFD(1.0 or 0.0)	CFD(0.5)
C_{max} (1.0) vs. (0.5)		
$\sum C_j$ (0.0) vs. (0.5)		
TO (1.0) vs. (0.5)		

Table 5 Average Performance and Control Limits in Control Charts for Trade-off Balancing

	X-bar			*X*-LCL			*X*-UCL		
	CFD(1.0)	CFD(0.0)	CFD(0.5)	CFD(1.0)	CFD(0.0)	CFD(0.5)	CFD(1.0)	CFD(0.0)	CFD(0.5)
C_{max}	**21.96**	86.93	27.20	**15.26**	75.55	17.74	**28.65**	98.31	36.67
$\sum C_j$	86.77	**20.78**	59.42	73.79	**12.15**	46.86	99.76	**29.40**	71.98
TO	54.37	53.86	**43.31**	46.94	45.82	**35.67**	61.79	61.89	**50.95**
	R			*R*-LCL			*R*-UCL		
	CFD(1.0)	CFD(0.0)	CFD(0.5)	CFD(1.0)	CFD(0.0)	CFD(0.5)	CFD(1.0)	CFD(0.0)	CFD(0.5)
C_{max}	**21.71**	36.91	30.70	**4.84**	8.23	6.85	**38.58**	65.59	54.56
$\sum C_j$	42.13	**27.98**	40.73	9.40	**6.24**	9.08	74.86	**49.73**	72.38
TO	**24.09**	26.06	24.78	**5.37**	5.81	5.53	**42.80**	46.31	44.04

Based on the number of out-of-control points in X-bar charts in Table 4, CFD(0.5) achieves zero out-of-control points on C_{max}, compared to 4 out-of-control points by CFD(1.0); both CFD(0.0,0.5) have out-of-control points on $\sum C_j$, and both CFD(1.0,0.5) have out-of-control points on TO.

In Table 5 the minimum values of average performance for X-bar and R, and relative control limits of LCL and UCL for X-bar and R, are highlighted in bold. Based on average performance of X-bar charts, we can see that CFD(0.5) can achieve a minimum value of 43.31 on min(TO), smaller than those of 54.37 and 53.86 for CFD(1.0) and CFD(0.0), respectively. Comparatively, the value achieved by CFD(0.5) is 27.20 on min(C_{max}), larger than that of 21.96 achieved by CFD(1.0), and the value of 59.42 by CFD(0.5) on min($\sum C_j$) is larger than that of 20.78 by CFD(0.0). For average performance of min(TO), CFD(0.5) also achieves minimum values on relative lower and upper control limits, but not minimum values on relative control limits for min(C_{max}) or min($\sum C_j$), respectively. Regarding X-LCL and X-UCL as "tolerance" limits on process performance, CFD(0.5) achieves good performance on trade-off balancing, allowing large variations of process performance on both min(C_{max}) and min($\sum C_j$). This conclusion is further supported by variation ranges R and relative control limits R-LCL and R-UCL, for each of which CFD(0.5) does not require minimum values.

Average computation times of CFD(0.5), NEH, LR, and FF heuristics are reported in seconds in Table 6 based on each scale of 10 instances in Taillard's benchmarks. The Matlab codes of all heuristics were run on a Dell Precision T1700 with 32.0 GB RAM and a CPU of 3.50 GHz. We recognize that computation speed is more accurately reflected based on the computational complexities of constructive heuristics, rather than on computation times, because computation times are often influenced by the configurations and software installed on the computer. Nevertheless, computation time can capture relative differences. The computational complexity of $O(n^3m)$ is implemented for the NEH, CFD and LR heuristics, and that of $O(n^2m)$ for the FF heuristic.

4.3. Historical OR Data from UKHC

Historical OR data from UKHC consists of almost 30,000 patient cases in 365 consecutive days spanning parts of 2013 to 2014. UKHC schedules ORs on weekdays, but opens emergency rooms on weekends and holidays, thus the number of patient cases on weekends

Table 6 Average Computation Times on Taillard's Benchmarks (Sec.)

n by *m*	CFD(0.5)	NEH	LR(1)	FF
20 by 5	0.02	0.00	0.03	0.00
20 by 10	0.02	0.00	0.04	0.00
20 by 20	0.01	0.00	0.03	0.00
50 by 5	0.05	0.00	0.17	0.00
50 by 10	0.06	0.00	0.16	0.00
50 by 20	0.05	0.01	0.16	0.00
100 by 5	0.17	0.01	0.58	0.00
100 by 10	0.21	0.04	0.67	0.00
100 by 20	0.25	0.07	0.72	0.01
200 by 10	1.11	0.29	3.16	0.06
200 by 20	1.45	0.59	4.03	0.10
500 by 20	18.91	9.79	53.18	0.60
Avg	1.86	0.90	5.24	0.07

and holidays is much less than that on weekdays. Excluding data points on weekends and holidays, we have more than 28,000 patient cases in 260 days used in our case study.

Recall that the periop process has three stages of preop, intraop and postop in series. In practice, utilization rates of the periop process and patient flow time across the periop process, or average completion time, are two metrics used to evaluate performance of OR scheduling methods. Maximizing utilization rates is closely related to the objective $\min(C_{max})$. In contrast, minimizing average patient flow time (PtF) is directly related to $\min(\sum C_j)/n$. The relative performance of the CFD, NEH, LR and FF heuristics on utilization ($Util$) and on PtF is provided in Table 7, and compared to that of UKHC.

Table 7 Utilization and Average Patient Flow Time

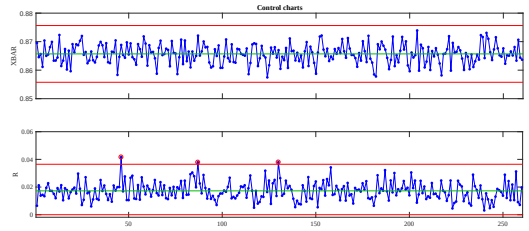
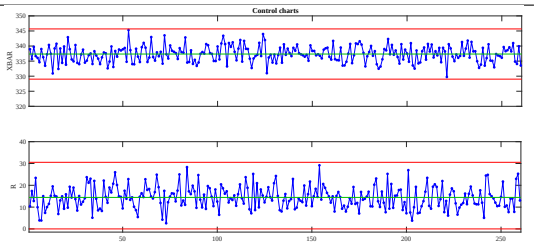
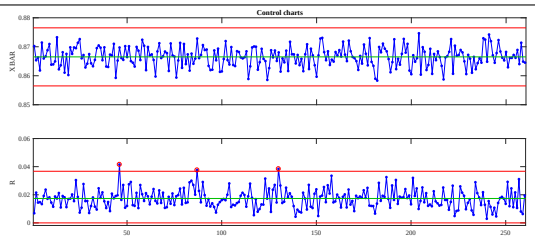
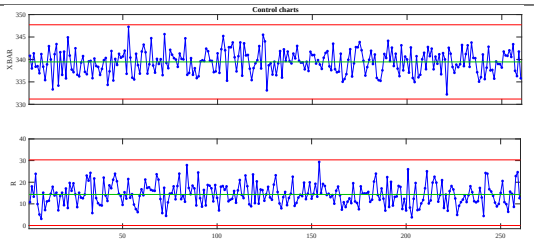
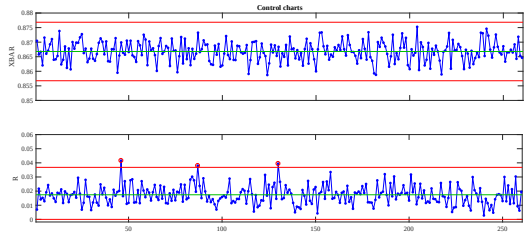
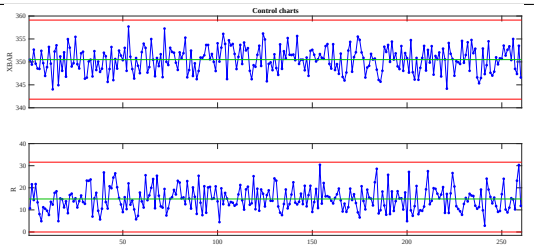
		CFD(0.0)	CFD(0.5)	CFD(1.0)	NEH	LR(1)	FF	UKHC
Util	Avg	86.57	86.65	**86.68**	86.68	86.53	86.51	86.60
	StD	**0.75**	0.76	0.76	0.76	0.75	0.75	0.75
	t-test	0.00	--	0.00	0.00	0.00	0.00	0.00
PtF	Avg	**337.35**	339.45	350.50	358.76	337.39	337.71	375.30
	StD	6.14	**6.07**	6.32	6.64	6.13	6.13	7.05
	t-test	0.00	--	0.00	0.00	0.00	0.00	0.00

In Table 7, we can see that the CFD(0.0,0.5,1.0) can achieve the best performance on $\max(Util)$, $\min(PtF)$ and $\min(StD)$, respectively. Defining a 2-tuple performance of $[Util, PtF]$, specifically, UKHC has a performance of $[86.60\%, 375.30]$, CFD(0.0) has a performance of $[86.57\%, 337.35]$, CFD(0.5) has a performance of $[86.65\%, 339.45]$, and

CFD(1.0) has a performance of [86.68%, 350.50]. Given the performance of [86.68%, 358.76], [86.53%, 337.39] and [86.51%, 337.71] for the NEH, LR and FF heuristics, respectively, we can see that CFD(1.0) dominates NEH, and CFD(0.0) dominates LR and FF, for OR scheduling based on *Util* and on *PtF* across the periop process. All scheduling methods are significantly different from each other based on p-values of t-tests against CFD(0.5).

To further verify that CFD(0.5) can keep the process better under control, we plot control charts of X-bar and R charts in Table 8 and provide the relative values of X-bar, R, and control limits in Table 9.

Table 8 Control Charts for Trade-off Balancing on UKHC Data

CFD(α)	Util	PtF
(0.0)		
(0.5)		
(1.0)		

For all three methods of CFD(0.0,0.5,1.0), there are no points out of control in X-bar charts for *Util* and *PtF* on UKHC data, although there are three points out of control in R charts for *Util*.

In addition to control charts, we further generate process capability charts in Table 10 for CFD(0.0,0.5,1.0) on *Util* and *PtF* to see if the periop process is better under control. According to Montgomery 2007, a process capability (C_p) is used to verify if the process

Table 9 Average Performance and Control Limits in Control Charts for UKHC Data

	***X*-bar**			***X*-LCL**			***X*-UCL**		
	CFD(0.0)	**CFD(0.5)**	**CFD(1.0)**	**CFD(0.0)**	**CFD(0.5)**	**CFD(1.0)**	**CFD(0.0)**	**CFD(0.5)**	**CFD(1.0)**
Util	86.57	86.65	86.68	85.58	85.65	85.68	87.57	87.65	87.68
PtF	337.35	339.45	350.50	329.02	331.18	341.88	345.68	347.73	359.11
	R			***R*-LCL**			***R*-UCL**		
	CFD(0.0)	**CFD(0.5)**	**CFD(1.0)**	**CFD(0.0)**	**CFD(0.5)**	**CFD(1.0)**	**CFD(0.0)**	**CFD(0.5)**	**CFD(1.0)**
Util	1.72	1.74	1.74	0.00	0.00	0.00	3.65	3.67	3.68
PtF	14.44	14.34	14.94	0.00	0.00	0.00	30.54	30.33	31.59

is under control, given $C_p = (USL - LSL)/(6 \cdot \sigma)$, where σ is the standard deviation of historical process performance, USL and LSL stand for upper and lower specification limits respectively, and are determined by schedulers based on historical performance. A process capability index (C_{pk}) is used to verify if the process drifts way from the average and tends to be out of control, given $C_{pk} = \min[(USL - \mu)/(3 \cdot \sigma), (\mu - LSL)/(3 \cdot \sigma)]$, where μ is the average of historical process performance. Given USL and LSL for expected performance, the larger the C_p and C_{pk} values, the smaller the process variation and the more centered the process is under control in terms of μ and σ. To compare the three methods of CFD(0.0,0.5,1.0) on trade-off balancing, we generate specifications according to the performance of $[86.65\%, 339.45]$ by CFD(0.5) with relative standard deviations of $[0.34, 2.62]$. Given tight specification limits with one standard deviation, the LSL and USL for $Util$ are $[86.31\%, 87.00\%]$, and for PtF are $[336.84, 342.07]$. Process capabilities of the three methods are summarized in Table 11.

Given the specification limits set up by the performance of CFD(0.5), in Table 10, we see that the $Util$ of CFD(0.5) is most centered, compared to that of CFD(0.0) shifting slightly to the right, and that of CFD(1.0) shifting slightly to the left. The probabilities of being within the specification limits for $Util$ in Table 11 support this observation, with the highest probability of 0.9696 for CFD(0.5), followed by 0.9681 for CFD(1.0) and 0.9668 for CFD(0.0). For PtF, CFD(0.5) keeps the process under control the best among the three methods, compared to that of CFD(0.0) shifting slightly to the right and that of CFD(1.0) shifting severely to the left. The probabilities of being within the specification limits for PtF supports this observation as well, with the highest probability of 0.9816 for CFD(0.5), followed by 0.9349 for CFD(0.0) and 0.0354 for CFD(1.0). Moreover, the negative C_{pk} value of -0.6022 for CFD(1.0) on PtF also indicates that the patient flow process is out of control if OR managers simply focus on $\max(Util)$.

Table 10 Process Capability Charts for Trade-off Balancing on UKHC Data

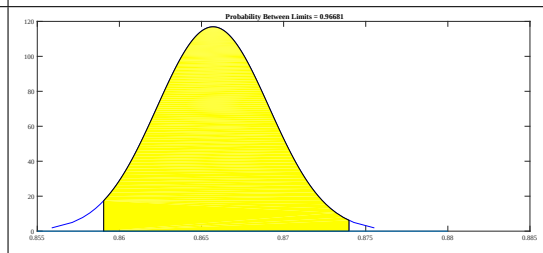
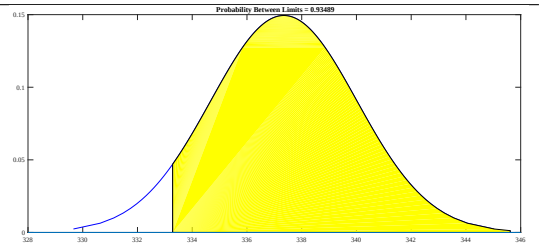
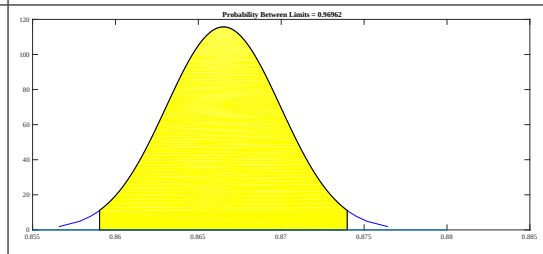
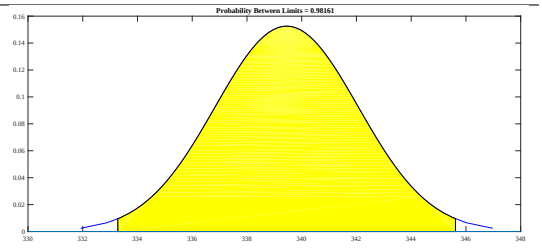
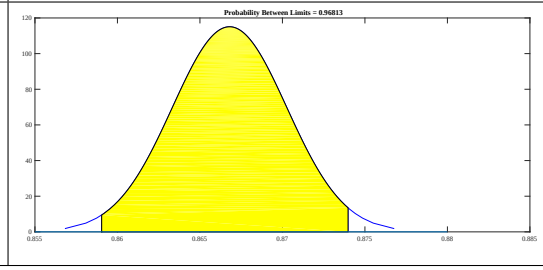
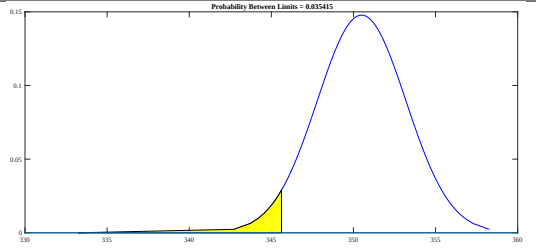
CFD(α)	Util	PtF
(0.0)		
(0.5)		
(1.0)		

Table 11 Process Capabilities for Trade-off Balancing on UKHC Data

	Specifications		**CFD(0.5)**	
	LSL	**USL**	μ	σ
Util	86.31	87.00	86.65	0.34
PtF	336.84	342.07	339.45	2.62

	C_p			C_{pk}			**Prob. between CFD(0.5) Specs**		
	CFD(0.0)	**CFD(0.5)**	**CFD(1.0)**	**CFD(0.0)**	**CFD(0.5)**	**CFD(1.0)**	**CFD(0.0)**	**CFD(0.5)**	**CFD(1.0)**
Util	0.7292	0.7217	0.7178	0.6504	0.7217	0.6903	0.9668	**0.9696**	0.9681
PtF	0.7698	0.7859	0.7613	0.5070	0.7859	-0.6022	0.9349	**0.9816**	0.0354

Overall, if the CFD(0.5) heuristic was used for OR scheduling across the periop process at UKHC, the process utilization could be slightly improved by $0.058\% = (86.65 - 86.60) \div 86.60$,which means some cost saving, and patient flow could be significantly improved by $9.552\% = (375.30 - 339.45) \div 375.30$, which indicates that potentially additional 2600 patients could be served in a year. Moreover, the performance of the periop process could be more stable based on the process capabilities of C_p and C_{pk}.

Table 12 Spearman's ρ among Sequences for Scheduling Objectives

Dataset	1.0 vs. 0.0	1.0 vs. 0.5	0.5 vs. 0.0
Small-scale instances	0.0897	0.2757	0.2193
UKHC historical data	0.0163	0.0197	0.1070
Taillard's benchmarks	0.0129	0.0425	−0.0039

4.4. Inconsistency among $\min(C_{max})$, $\min(\sum C_j)$ and $\min(TO)$

To empirically confirm the inconsistency between $\min(C_{max})$ and $\min(\sum C_j)$ we show that the sequences for these two objectives are uncorrelated with one another, and with the one for $\min(TO)$, we run our CFD heuristic with $\alpha = \beta = 1.0$ to generate the sequence for $\min(C_{max})$, with $\alpha = \beta = 0.0$ to generate the sequence for $\min(\sum C_j)$, and with $\alpha = \beta = 0.5$ to generate the sequence for $\min(TO)$. We do this for all three of our datasets: small-scale instances, Taillard's benchmarks and UKHC historical OR records. For each of the datasets we compute the Spearman rank correlation coefficient ρ between the sequences, and these results are shown in Table 12.

In Table 12, the column 1.0 vs. 0.0 refers to the correlation between $\min(C_{max})$ and $\min(\sum C_j)$, the column 1.0 vs. 0.5 refers to the correlation between $\min(C_{max})$ and $\min(TO)$, and the column 0.5 vs. 0.0 refers to the correlation between $\min(TO)$ and $\min(\sum C_j)$. It is obvious that an inconsistency exists between the sequences generated to $\min(C_{max})$ and $\min(\sum C_j)$ with small Spearman rank correlation coefficients that are not significantly different from zero for all three datasets. Specifically for correlation between $\min(C_{max})$ and $\min(\sum C_j)$, the Spearman ρ is 0.0897 for small-scale instances, 0.0163 for UKHC historical data, and 0.0129 for Taillard's benchmarks.

This lack of correlation, positive or negative, between the two sequences generated to $\min(C_{max})$ and $\min(\sum C_j)$ suggests that the two objectives are relatively orthogonal in implementation. This orthogonality reinforces the value of trade-off balancing in bi-criteria scheduling: in its implementation our CFD heuristic incorporates characteristics of different objectives, and improves performance even when sequences generated by the underlying objectives are uncorrelated.

As the number of jobs n is small, the number of factorial of n, $n!$, sequences is small. Therefore, the empirical inconsistencies between $\min(C_{max})$ and $\min(TO)$ and between $\min(TO)$ and $\min(\sum C_j)$ are less obvious: the Spearman ρ is 0.2757 and 0.2193, respectively, for small-scale instances. As the number of machines or stages m is small, but n is

large, the empirical inconsistency between $\min(C_{max})$ and $\min(TO)$ is obvious for UKHC historical data with a Spearman ρ of 0.0197, but that between $\min(TO)$ and $\min(\sum C_j)$ is less obvious with a Spearman ρ of 0.1070. However, as both n and m are large, the empirical inconsistencies between $\min(C_{max})$ and $\min(TO)$ and between $\min(TO)$ and $\min(\sum C_j)$ are obvious for Taillard's benchmarks with the Spearman ρ of 0.0425 and -0.0039, respectively. Such lack of pairwise correlation between sequences generated among three objectives indicate that process design should take the number of jobs and the number of operations into consideration. For example, if the periop process at UKHC was separated into more than three stages, or a stage was finely tuned into several operations, the inconsistency between $\min(TO)$ and $\min(\sum C_j)$ might be obvious as well.

5. Conclusion and Future Work

Given the property of NP-completeness for each of $\min(C_{max})$ and $\min(\sum C_j)$ scheduling problems, we model the trade-offs by two coupled deviations, providing an innovative and systematic approach for modeling scheduling problems for serial processes. Based on this new approach to model scheduling problems, we provide an effective interpretation concerning deviations at the operation level and at the process level, where current deviations should be taken into consideration for $\min(C_{max})$, but both current and future deviations should be considered for $\min(\sum C_j)$. This is because maximum completion time is purely determined by the sum of idle times for deterministic problems, and future idle times in U are influenced by current completion times of jobs in S, but not the other way around. However, total completion time is determined by the sum of weighted idle times and weighted processing times, which means jobs in both S and U interact with each other on $\min(\sum C_j)$.

Our systematic approach of analyzing two coupled deviations in our heuristic development helps us address the concern about dominance evaluation as in Pareto efficiency, whereby we should put equal preferences for balancing trade-offs between $\min(C_{max})$ and $\min(\sum C_j)$. This answers the first question that near-optimal solutions to $\min(C_{max})$ or to $\min(\sum C_j)$ cannot balance the trade-offs given the inconsistency between simple objectives. Modelling coupled deviations from upper and lower bounds of completion times by α, and balancing trade-offs between output variables by β, means our CFD heuristic is sufficiently flexible to address management concerns at both operation and process levels.

Through case studies on 5400 small-scale instances, our CFD heuristic outperforms the NEH, LR, and FF heuristics on trade-off balancing, and on $\min(C_{max})$ and $\min(\sum C_j)$, respectively. Through case studies on 120 instances in Taillard's benchmarks, the FF heuristic marginally outperforms our CFD heuristic only on $\min(\sum C_j)$, but not on our other performance metrics, and our CFD heuristic outperforms the NEH and LR heuristic on all of our performance metrics.

Our approach to model trade-offs between $\min(C_{max})$ and $\min(\sum C_j)$ and our CFD heuristic provide a solid starting point for balancing trade-offs in serial processes, especially for OR scheduling across the periop process. Based on case studies of Taillard's benchmarks and historical OR data at UKHC, trade-off balancing can keep the process better under control, where the average trade-off values vary in a tight range, but with wider variation ranges allowable for C_{max} and for $\sum C_j$, respectively, the utilization and the patient flow time are improved across the periop process, and the periop process is more under control using our CFD heuristic for scheduling.

Dynamically updating the lower and upper bounds of completion times at the process level is part of our future work in heuristic development for better trade-off balancing. This is because our analysis of deviations is more effective for small-scale instances, on which our CFD heuristic clearly dominates the NEH, LR and FF heuristics on $\min(C_{max})$ and $\min(\sum C_j)$, respectively, but less effective on $\min(\sum C_j)$ for Taillard's benchmarks.

Acknowledgments

This project was supported by grant number R03HS024633 from the Agency for Healthcare Research and Quality. The content is solely the responsibility of the authors and does not necessarily represent the official views of the Agency for Healthcare Research and Quality. We appreciate support from UK HealthCare, the Department of Mechanical Engineering at University of Kentucky, the Natural Sciences and Engineering Research Council of Canada, and the Haskayne School of Business at University of Calgary. We thank Jeanette Burman for editing assistance.

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