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Stability of trade-off balancing in one-stage production scheduling

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Abstract

Production scheduling faces three challenges, which are inconsistent key performance indicators (KPIs), processing time uncertainties, and production schemes. Applying modern portfolio theory (MPT), Li et al. (2021) proposed a ToB(α) heuristic to balance trade-offs in one-stage production. However, production schemes for optimizing average performance of individual KPIs, trade-off values, or worst-case scenarios affect the stability of a process differently, especially with processing time uncertainties. We propose an innovative approach using transfer functions for stability (TF4S) in balancing trade-offs in production scheduling. Our TF4S approach provides a systematic way to analyze the stability of one-stage production and can be extended to production scheduling for classic *m*-machine flow lines.

Keywords: Production scheduling; Stability; Trade-off balancing; Transfer function;

1. Introduction

Production scheduling involves the allocation of competing tasks to scarce resources over time in achieving some objectives [1]. Given limited resources, it is difficult to achieve the optimum across each of individual objectives, especially when objectives are inconsistent with each other. Inconsistent key performance indicators (KPIs) exist in both *N*-job one-stage production and classical *N*-job *m*-machine flowshop production. Consequently, multi-objective optimization is a challenge for production scheduling.

Stochastic processing times are ubiquitous in many processes for different systems, such as in production lines for manufacturing, in perioperative processes for operating room scheduling, and in supply chains. Given diversified system settings, it is impossible at current time *t* to know the exact value of a stochastic processing time for time *t*+1 [2]. Although we can describe stochastic processing times by different distributions, outliers always exist. In addition, measurement errors may fail our prediction. Therefore, processing time uncertainty is another challenge for production scheduling.

Many optimization problems in production scheduling are *NP*-complete or *NP*-hard in strong sense, such as minimizing maximum completion time or makespan for a classic flow line with more than 2 machines [3], minimizing total completion time for two-stage processes [4], and minimizing variance in processing times in one-stage production [5]. For *NP* problems, it is difficult to balance trade-offs between two inconsistent KPIs. For example, in operating room (OR) scheduling, speeding up the patient flow (or reducing patient flow time) going through ORs might cause idle time in ORs and reduce OR utilization. Consequently, maximizing OR utilization and minimizing patient flow time are inconsistent with each other. Moreover, maximizing OR utilization and minimizing patient flow time are *NP*-complete problems, without polynomials for optimization. Consequently, it is difficult to quantify how much patient flow time we should sacrifice to improve OR utilization, and vice versa. Similarly, in manufacturing, reducing work-in-process (WIP) inventory is inconsistent with maximizing utilization of production lines, each of which is also an *NP* problem. Given such properties of *NP*-completeness or *NP*-hardness for some KPIs, optimizing the

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worst-case scenario is a common scheme in production scheduling to hedge against processing time uncertainties. However, Li et al. empirically showed that optimizing the worst-case scenarios does not necessarily optimize the expected value of KPIs [6]. What scheduling scheme should be adopted for production is the third challenge for production scheduling.

Given the above three challenges to production scheduling, which are inconsistent KPIs, processing time uncertainties, and production schemes, we propose an approach of transfer functions for stability (TF4S) in balancing trade-offs for one-stage production. Our TF4S provides a systematic way to analyze one-stage production performance, and it can be extended to production scheduling for classic flow lines.

The rest of this paper is organized as follows. A brief literature review is provided in Section 2, the programming logic of our TF4S approach is illustrated in Section 3, results of empirical case studies are analyzed in Section 4, and conclusion and future work are detailed in Section 5.

2. Literature review

Inconsistent KPIs in production are provided in subsection 2.1, especially for one-stage production, common scheduling schemes are summarized in subsection 2.2, a few existing scheduling methods for production with stochastic processing times are discussed in subsection 2.3 especially for trade-off balancing, and the concepts of transfer function and process stability are summarized in subsection 2.4.

2.1. Inconsistent KPIs in production

Given N jobs for one-stage production, we denote p_j for processing times of job $j = 1,\ldots,N$. Total completion time (*TCT*) is a fundamental KPI in production scheduling. For instances with deterministic processing times,

$$TCT = \sum_{j=1}^{N}(N - j + 1) \cdot p_j, \tag{1}$$

is a weighted sum of processing times, and weights $(N - j + 1)$ are not dependent on processing times, but on the order of jobs in a sequence. Consequently, if we use the shortest processing time (SPT) rule to sort processing times into a non-decreasing order, then we have an optimal solution to min(*TCT*) for deterministic instances. As mean flow time equal to *TCT*/*N* is the average completion time, min(*TCT*) drives other KPIs, such as the average of WIP inventories in production and the mean waiting time in perioperative processes.

Although minimizing *TCT* can be modelled as a polynomial of Eq. (1) for deterministic instances, minimizing the variance in completion times (*VCT*) is *NP*-hard in general [5]. To min(*VCT*), Schrage (1975) found that the job with the longest processing time (LPT) should be sequenced first [7]. The SPT and LPT rules sequence processing times into different shapes, which shows the inconsistency between min(*TCT*) and min(*VCT*) empirically. Moreover, Eilon and Chowdhury (1977) found that the optimal sequence to min(*VCT*) must be V-shaped [5], i.e., the jobs must be arranged in a descending order of processing times if they are scheduled before the job with the shortest processing time, but in an ascending order of processing times if scheduled after it, which is the combination of LPT and SPT rules. Kanet (1981) found an alternative way to min(*VCT*), which is equivalent to measuring the total absolute differences in completion times (*TADC*) [8],

$$TADC = \sum_{j=1}^{N}(j - 1)(N - j + 1) \cdot p_j. \tag{2}$$

Equations (2,3) illustrate the trade-offs between minimizations of *TCT* and *VCT*, where $(N - j + 1)$ is a linear function of j, but $(j - 1)(N - j + 1)$ is a quadratic function.

For N-job M-machine flowshop production, we denote $p_{j,i}$ for processing time of job j on machine $i = 1,\ldots,M$. Minimizing maximum completion time (*MCT*), $C_{max} = C_{N,M}$ or makespan, is a common KPI in production scheduling, driving many other performance measures, such as machine utilization, production cost, etc. Li et al. (2014) proved the inconsistency between min(*MCT*) and min(*TCT*) [9]. Using a 2-machine flow line, Li et al. showed that one condition of $p_{j,2} - p_{j+1,2} \leq 0$ is good for min(*TCT*), but another condition of $p_{j+1,2} - p_{j,2} \leq 0$ is good for min(*MCT*).

Current research on flow shop scheduling (2005-present) has extended to sustainability in terms of energy-efficiency, water usage, CO_2 emission [10][11][12][13], which intensifies the need for balancing trade-offs among inconsistent KPIs.

2.2. Common scheduling schemes against uncertainties

One of the difficulties in handling stochastic processing times is that the actual value of a processing time is not available in advance, but known only after the operation is finished [2]. Consequently, simulation is the general offline approach to investigate stochastic problems. The coefficient of variation, $CV = \sigma / \mu$, is commonly used to describe variation levels in processing times, where σ is the standard deviation of a random variable, and μ is the mean.

In general, as *CV* increases, the process performance for production gets worse. Conway et al. (1988) investigated the effect of WIP inventories in flowshop production [14]. Through simulation, they concluded that the larger the *CV*, the lower the capacity of a production line, and WIP inventories were important to recover the capacity.

Adaptive control is a dynamic approach for stochastic problems, which means re-sequencing jobs online as soon as actual processing times are available. However, because of high demand on computation speed for online re-sequencing, Lawrence and Sewell (1997) recommended simple priority dispatching rules (PDRs) over sophisticated heuristics for adaptive control with variation in processing times [15]. Cao, Patterson, and Bai (2005) and Mahmoodi, Mosier, and Guerin (1996) recommended the SPT rule to minimize the mean flow time and WIP inventory levels for deterministic instances [16][17]. Conway et al. (1967) recommended the shortest expected processing time (SEPT) to min(*TCT*) for stochastic instances [18].

Optimizing worst-case scenarios is a common scheme in simulation for offline scheduling. Maximizing minimum deviations from the upper bound of a KPI is the same as minimizing maximum deviation from the lower bound. Daniels and Kouvelis (1995) proposed the endpoint product (EP) and endpoint sum (ES) heuristics to hedge against processing time uncertainties in one-stage production [19]. These two heuristics are designed to maximize minimum deviations from the upper bound of *TCT*, i.e., generating robust schedules for the worst-case scenarios accordingly. Similarly, Rahmani and Heydari (2014) proposed a regret model to optimize the worst-case scenarios of min(*MCT*) in *M*-machine flowshop production [20].

2.3. Some scheduling methods for stochastic processing times

Modern portfolio theory (MPT) proposed by Markowitz (1952) was originally used to balance trade-offs between the expected returns and the risks involved in investment [21]. Applying the MPT model to production scheduling, Li et al. (2021) linked a factor α with *VCT*, and proposed a trade-off balancing heuristic, ToB(α), to balance trade-offs between min(*TCT*) and min(*VCT*) in one-stage production [6]. Through case studies with the *CV* changing from 0.0 to 0.5 for uniform distributions, the ToB(α) heuristic outperformed the EP and ES heuristics in terms of the expected values of *TCT*, and it achieved smaller maximum deviations from the lower bound at *CV* = 0.5, which means being more robust when processing time uncertainty is high.

Li and Freiheit (2016) proposed a 'state space-average processing time' (SS-APT) heuristic to min(*MCT*) for *N*-job *M*-machine flow shop production with stochastic processing times [2]. The SS-APT heuristic is used to re-sequence jobs online for adaptive control. Through case studies, Li and Freiheit concluded that their heuristic performed better than simple PDRs on adaptive control, especially for WIP inventories.

2.4. Transfer function and stability

We have one concern about existing scheduling methods, which is how they perform for stochastic processing times in distributions other than uniform or truncated normal distributions, or for a real situation where processing time uncertainty is higher than that in simulation.

A transfer function of a system or a process is a mathematical function that theoretically models the output for each possible input [22]. A transfer function can be expressed either in the time domain or in the frequency domain. Define the output Y as related to the input X by a transfer function H, in terms of $Y(s) = H(s)\ X(s)$, where $s = j\omega$ is a variable in frequency domain. $H(s) = Y(s)\ /\ X(s) = N(s)\ /\ D(s)$ is the transfer function, where $N(s)$ is a polynomial for the numerator and $D(s)$ for the denominator. The solutions to the characteristic function of $D(s) = 0$ are called the poles (λ). If the real parts of the poles are on the left half plane of the complex plane, i.e., $\mathrm{Re}(\lambda) < 0$, then the system is stable.

Bode plots are generally used to assess the stability of a negative feedback loop, in which the gain margin (*Gm*) and phase margin (*Pm*) are required to maintain stability under variations caused by uncertainties or disturbances involved in a process. Specifically, the gain margin is the change in open-loop gain, expressed in decibels (dB), required at 180° of phase shift to make the closed-loop system unstable, and the phase margin is the change in open-loop phase shift required at unity gain to make the closed-loop system unstable [22]. The gain margin is found by using the phase plot to find the frequency, ω_{Gm}, where the phase angle is 180°. On the magnitude plot at this frequency, the gain margin, *Gm*, is the gain required to raise the magnitude curve to 0 dB. The phase margin is found by using the magnitude curve to find the frequency, ω_{Pm}, where the gain is 0 dB. On the phase plot at this frequency, the phase margin, *Pm*, is the difference between the phase value and 180°.

In general, the larger the gain and phase margins, the higher is the stability of a process to hedge against external disturbances or internal uncertainties.

3. Transfer function for stability in trade-off balancing

Given processing time uncertainties, in terms of different distributions with different magnitudes and frequencies, a transfer function is helpful for us to investigate the properties of a process through scheduling. Currently, major literature on production scheduling is either to seek near-optimal solutions to *NP* problems by using heuristics, or to improve the computation speed or reduce computational complexities of sequencing methods by better searching the solution space. We have not seen any publication that addresses the stability of production using transfer functions, especially from the perspective of control theory. In contrast, research on transfer functions for stability in control theory is mainly based on polynomial problems.

Assigning a factor of α to Eq. (2) as the preference on min(*VCT*) and another factor of (1 – α) to Eq. (1) as the preference on min(*TCT*), Li et al. (2021) used the following equation to sequence jobs in the ToB(α) heuristic for trade-off balancing in one-stage production [6]:

$$z = \sum_{j=1}^{N} [(j-2)\alpha + 1](N - j + 1) \cdot p_j. \tag{3}$$

As both *TCT* and *VCT* are driven by completion times, we can regard a vector of N completion times as output Y from one-stage production, which is related to weights W and processing times P as input X associated with job $j = 1,\dots,N$. Defining input as $X = [P, W]$, we have the relationship of $Y(j) = H(j)X(j)$. To estimate transfer function $H(j)$, we apply an autoregressive and moving average, $ARMA(a,b)$ model, in time series analysis to estimate $H(j)$. Specifically, an $ARMA(a,b)$ process is defined as follows [23]:

$$\begin{aligned} Y_j = c + \phi_1 Y_{j-1} + \phi_2 Y_{j-2} + \cdots + \phi_a Y_{j-a} + \\ \varepsilon_j + \theta_1 \varepsilon_{j-1} + \theta_2 \varepsilon_{j-2} + \cdots + \theta_b \varepsilon_{j-b}, \end{aligned} \tag{4}$$

where c is a constant, e.g., average completion time, ε_j can be difference between X_j and its mean, i.e., the error term, ϕs and θs are coefficients for output series Y and error series ε, and a and b are two integer constants for lags in Y and ε, respectively. Define a lag operator L such that $LX_j = X_{j-1}$ and $L(LX_j) = L^2X_j = X_{j-2}$. Using the lag operator, we can rearrange terms in Eq.(4) and have

$$\begin{aligned} (1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_a L^a) Y_j \\ = c + (1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_b L^b)\varepsilon_j. \end{aligned} \tag{5}$$

Provided that the roots for $1 - \phi_1 z - \phi_2 z^2 - \cdots - \phi_a z^a = 0$ lie outside the unit circle, where z is a real number for the polynomial of $\phi\,(z)$, we can divide both sides of Eq.(5) by $(1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_a L^a)$ and obtain $Y_j = \mu + H(L)\varepsilon_j$, where $\mu = c/(1 - \phi_1 - \phi_2 - \cdots - \phi_a)$, and

$$H(L) = \frac{(1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_b L^b)}{(1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_a L^a)}. \tag{6}$$

Consequently, $H(L)$ is in the form of a transfer function that relates output ($Y_j - \mu$) with input ε_j, and stationarity of the *ARMA* process depends entirely on the autoregressive parameters ($\phi_1, \phi_2, \ldots, \phi_a$), the same as the poles of $H(s)$ for the stability of a system. Moreover, sequencing jobs for production scheduling can be specifically based on the $AR(a)$ series for differences of output Y and on the $MA(b)$ series for differences of input X, which can be regarded as polynomials describing the relationship between input and output.

Provided a transfer function H of a stage, it is flexible and easy to link multiple stages in series to form a flow line, or to add a feedback loop to a stage for adaptive control. For example, linking two stages H_1 and H_2 in series, we can describe the transfer function H of the two-stage flow line as the product of two transfer functions, i.e., $H = H_1 H_2$. Adding a unity negative feedback loop to H, the new transfer function for the closed-loop stage is $G = H / (1 + H)$. Therefore, we are able to provide a systematic approach to analyze the production stability of a process by means of scheduling.

4. Case studies

To verify the stability of trade-off balancing in one-stage production, we generate an N-job one-stage dataset as follows. The number of jobs range from N = 500, 1000, 2000 with a number of 50 instances for each. The total number of instances is $I = 150 = 3 \cdot 50$. The processing times for each instance follows a uniform distribution between [1, 999]. The stochastic processing times are randomly generated, using the processing times of an instance as the expected values $E(p)$ and following a uniform distribution. Accordingly, an observation in a sample is determined by $p = E(p) + \sqrt{3}E(p)CV(2U - 1)$, where U is a uniform random number from [0, 1]. In order to ensure that processing times do not fall below zero when using a uniform distribution, a condition of $CV \leq 1/\sqrt{3}$ should be maintained. The CV changes from 0.1 to 0.5 with increments of 0.1 and S = 50 samples for each CV and for each instance. The total number of samples is $37{,}500 = 150 \cdot 5 \cdot 50$.

In total, 16 sequences are generated for each sample, with 11 by the ToB(α) heuristics each with different α, and 1 by each of the EP, ES, SEPT, longest expected processing time (LEPT) and first come first serve (FCFS) methods, respectively. Among these 16 heuristics, our ToB, SEPT and LEPT heuristics operate on expected processing times, the EP and ES heuristics operate on lower and upper limits of processing times, and the FCFS does not depend on processing times.

We present case study results for estimating a transfer function in subsection 4.1, for the stabilities of open and closed loops in subsection 4.2, for the gain and phase margins in subsection 4.3, and for 5 *CV*s in subsection 4.4. In three subsections of 4.1, 4.2, and 4.3, the results are across preference factor α = 0.0, 0.1, 0.2,…, 1.0, and the results in subsection 4.4 are across CV = 0.1, 0.2,…, 0.5.

4.1. Transfer function estimation

Given Eq. (3) for trade-off balancing, two factors affect the change rate in trade-off values and that in completion times. One factor is the sequence of processing times. Different scheduling methods sort processing times into different sequences of jobs, which affect the change rate in processing times. The other factor is the preference α on one KPI, which affects the change rate in weights. Given N jobs for one-stage production, we have N data points for completion times, weights as shown in Eq. (3), and processing times. We use 70% of our data points for estimating a transfer function (TF), and the remaining 30% for validating the TF model. These data points are based on nominal values of processing times for 150 instances, not based on those for 37,500 randomly generated samples. The probabilities that a TF model fits the validation data are reported in Table 1.

In Table 1, the preferences of α are listed in column 1, categories of statistics for maximum, minimum and average are listed in column 2 for each α, and the rest of the columns is for the 16 heuristics. From Table 1, we can tell that maxima of probabilities to fit the validation data are above 99% across all 11 preferences α and all 16 heuristics. Scheduling methods of ToB(0.0), EP, ES, and SEPT are not sensitive to the changes of preference α, as their averages of probabilities are above 99%. However, the value of preference α affects minima of probabilities differently with respect to heuristics. When α = 0.0, i.e., 100% preference on min(TCT), the LEPT's minimum of probability falls to 85.14 and that for FCFS is 93.80, because the LEPT rule is not good to min(TCT) and the FCFS does not control job sequencing. As α increases, i.e., more preference on min(VCT), the minima of probabilities have a decreasing trend in general.

In conclusion, it is feasible to estimate transfer functions for a heuristic for trade-off balancing, although some methods are sensitive to weights.

4.2. Stabilities of open and closed loops

To estimate the stability of an open loop, we calculate the two poles of a transfer function, and the maxima of two poles for 16 scheduling methods are reported in Table 2. From Table 2, we can tell that all poles are on the left half of the complex plane. Therefore, the transfer function for the open loop of the process is stable for all 150 instances.

We also check the stability of the transfer function with a unity negative feedback loop. The number of stable instances with a closed loop is reported in Table 3 across 150 instances, 11 preferences and 16 scheduling methods. From Table 3, we can tell, as the preference α increases, the number of stable instances increases in general, except for the LEPT rule, the number of stable instances for which decreases. As α increases, we prefer min(VCT) more than min(TCT). However, the process of production scheduled by the LEPT rule is very sensitive to the increase of such preferences.

In conclusion, we can achieve the stability of production with an open or closed loop by using a transfer function.

4.3. Gain and phase margins of closed-loop transfer functions

Another measure to evaluate the stability of a process is by gain and phase margins of a transfer function with either an open or closed loop. As adaptive control is often based on a closed loop, the gain and phase margins of a transfer function with a unity negative feedback loop are reported in Tables 4 and 5, respectively.

From Table 4 for gain margins, we can tell that all transfer functions have some gain margins on average, although the minima of gain margins are all 0 as $\alpha \geq 0.1$, which explains why the number of stable instances is less than 150 in Table 3.

From Table 5 for phase margins, we can tell all transfer functions have some phase margins on average, although the minima of phase margins are small across all preferences α.

Given that gain and phase margins are used to buffer the magnitude and frequency of uncertainties or disturbances, respectively, designing the gain of a controller in a closed loop will change the gain and phase margins for adaptive control, and scheduling affects the gain of a controller.

A Bode plot is provided in Fig. 1, which is one of 150 instances and based on the ToB(0.0) heuristic.

4.4. Stabilities across CVs

As different preferences α on KPIs affect the stability of a process differently, shown in Tables 4 and 5, we select $\alpha = 0.5$, i.e., an even preference on KPIs, to examine how processing time uncertainties affect the stability of a process. The average gain and phase margins across 5 *CV* levels for all instances and samples are provided in Tables 6 and 7, respectively.

From Table 6, we can tell that, with even preferences on KPIs, the grand averages of gain margins across all 5 *CV* levels are comparatively similar to the average gain margins in Table 4 for $\alpha = 0.5$, although fluctuations occur for individual scheduling methods in Table 6 across *CV* levels. The same properties are observed for the grand averages of phase margins in Table 7 compared to the average phase margins in Table 5.

For clarity, trend plots for gain and phase margins are provided in Fig. 2 and Fig. 3 respectively, not based on all methods, but on ToB(0.0, 0.5, 1.0), LEPT and FCFS.

These results support our use of transfer functions to investigate the stability of a process with high processing time uncertainties.

5. Conclusion and future work

Balancing trade-offs in production scheduling faces three challenges, which are inconsistent KPIs, processing time uncertainties, and production schemes. To answer these three challenges, we propose an innovative TF4S approach, to investigate the stability of a process by using transfer functions. Based on good scheduling results generated from the ToB(α) heuristics, our TF4S approach is consistent in balancing trade-off in one-stage production and in maintaining stability across 5 *CV* levels of processing time uncertainties.

Adaptive sequencing is the next step of our research, i.e., dynamically schedule jobs as actual processing times unfold in real time.

Table 1. Probabilities to fit validation data across preferences α for 16 scheduling methods.

α		ToB(α)											EP	ES	SEPT	LEPT	FCFS
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0					
0.0	Max	99.97	99.96	99.96	99.95	99.95	99.95	99.95	99.95	99.95	99.95	99.94	99.97	99.97	99.97	99.89	99.67
	Min	98.27	98.78	98.65	98.60	98.54	98.51	98.51	98.51	98.51	98.51	98.45	98.27	98.27	98.27	85.14	93.80
	Avg	99.86	99.31	99.25	99.23	99.22	99.20	99.20	99.20	99.20	99.20	99.19	99.86	99.86	99.86	99.13	98.62
0.1	Max	99.99	99.61	99.48	99.44	99.39	99.34	99.34	99.34	99.34	99.34	99.31	99.99	99.99	99.99	99.86	99.63
	Min	96.40	61.32	60.78	60.76	60.69	60.65	60.65	60.65	60.65	60.65	60.59	96.40	96.40	96.40	68.90	73.86
	Avg	99.84	86.00	82.86	82.18	81.59	80.98	80.98	80.98	80.98	80.98	80.10	99.84	99.84	99.84	92.02	97.67
0.2	Max	99.99	99.25	99.12	98.84	98.40	97.82	97.82	97.82	97.82	97.82	94.33	99.99	99.99	99.99	99.70	99.44
	Min	98.98	0.68	2.70	2.76	2.84	0.55	0.55	0.55	0.55	0.55	1.50	98.98	98.98	98.98	78.59	68.35
	Avg	99.88	64.60	68.32	67.40	66.71	66.20	66.20	66.20	66.20	66.20	67.71	99.88	99.88	99.88	91.10	97.55
0.3	Max	99.99	99.43	96.37	97.80	95.36	89.84	89.84	89.84	89.84	89.84	90.69	99.99	99.99	99.99	99.44	99.39
	Min	99.28	10.70	20.24	34.86	4.40	14.26	14.26	14.26	14.26	14.26	4.44	99.28	99.28	99.28	64.32	90.02
	Avg	99.87	72.60	73.24	73.13	72.06	71.34	71.34	71.34	71.34	71.34	71.12	99.87	99.87	99.87	88.52	97.66
0.4	Max	99.99	98.77	90.26	89.34	90.60	90.34	90.34	90.34	90.34	90.34	90.09	99.99	99.99	99.99	99.34	99.27
	Min	99.46	1.45	1.38	1.09	4.72	0.17	0.17	0.17	0.17	0.17	0.27	99.46	99.46	99.46	28.62	90.52
	Avg	99.87	74.14	71.87	72.74	73.77	74.02	74.02	74.02	74.02	74.02	71.27	99.87	99.87	99.87	82.66	97.75
0.5	Max	99.99	99.29	99.20	98.80	98.52	98.60	98.60	98.60	98.60	98.60	99.13	99.99	99.99	99.99	99.73	99.22
	Min	98.84	0.01	1.00	0.02	0.05	1.72	1.72	1.72	1.72	1.72	2.78	98.84	98.84	98.84	53.46	92.77
	Avg	99.82	56.79	62.29	65.23	65.81	71.11	71.11	71.11	71.11	71.11	72.68	99.82	99.82	99.82	84.38	97.66
0.6	Max	99.99	99.48	99.90	98.93	99.37	99.54	99.54	99.54	99.54	99.54	98.22	99.99	99.99	99.99	99.69	99.07
	Min	98.82	3.95	1.49	1.39	0.96	0.23	0.23	0.23	0.23	0.23	0.38	98.82	98.82	98.82	24.85	90.30
	Avg	99.80	54.15	53.27	53.69	57.57	56.37	56.37	56.37	56.37	56.37	56.77	99.80	99.80	99.80	81.77	97.38
0.7	Max	99.99	99.63	98.72	99.66	99.96	99.85	99.85	99.85	99.85	99.85	99.85	99.99	99.99	99.99	99.68	99.00
	Min	98.35	0.21	1.24	2.06	2.15	1.37	1.37	1.37	1.37	1.37	0.77	98.35	98.35	98.35	50.73	84.09
	Avg	99.79	52.17	47.75	47.98	49.49	52.07	52.07	52.07	52.07	52.07	52.45	99.79	99.79	99.79	92.62	96.84
0.8	Max	99.99	90.56	99.86	99.85	99.86	99.91	99.91	99.91	99.91	99.91	99.95	99.99	99.99	99.99	99.72	99.18
	Min	97.60	2.30	0.88	0.48	0.09	0.54	0.54	0.54	0.54	0.54	0.54	97.60	97.60	97.60	76.54	89.63
	Avg	99.79	44.99	49.55	48.81	50.04	53.01	53.01	53.01	53.01	53.01	52.12	99.79	99.79	99.79	95.18	97.01
0.9	Max	99.99	82.20	99.95	99.94	99.94	99.94	99.94	99.94	99.94	99.94	99.95	99.99	99.99	99.99	99.71	99.20
	Min	97.14	2.91	1.65	0.45	0.27	0.18	0.18	0.18	0.18	0.18	0.04	97.14	97.14	97.14	70.32	87.29
	Avg	99.80	41.84	48.52	48.40	48.34	49.97	49.97	49.97	49.97	49.97	50.05	99.80	99.80	99.80	95.03	97.29
1.0	Max	99.99	92.49	99.72	99.79	99.78	99.34	99.34	99.34	99.34	99.34	99.19	99.99	99.99	99.99	99.71	99.22
	Min	89.51	1.99	0.21	0.91	0.65	0.35	0.35	0.35	0.35	0.35	0.17	89.51	89.51	89.51	71.31	94.61
	Avg	99.63	35.73	42.95	43.32	44.70	45.05	45.05	45.05	45.05	45.05	44.94	99.63	99.63	99.63	93.99	97.60

Table 2. Maxima of two poles of a transfer function with an open loop for 16 scheduling methods.

α	ToB(α)											EP	ES	SEPT	LEPT	FCFS
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0					
0.0	-4E-8	-1E-3	-5E-4	-4E-4	-2E-4	-2E-4	-2E-4	-2E-4	-2E-4	-2E-4	-7E-5	-4E-8	-4E-8	-4E-8	-2E-8	-3E-6
0.1	-1E-8	-2E-6	-2E-6	-3E-6	-4E-6	-4E-6	-4E-6	-4E-6	-4E-6	-4E-6	-4E-6	-1E-8	-1E-8	-1E-8	-8E-6	-1E-5
0.2	-5E-7	-1E-6	-5E-6	-4E-6	-1E-6	-1E-6	-1E-6	-1E-6	-1E-6	-1E-6	-1E-6	-5E-7	-5E-7	-5E-7	-3E-5	-8E-7
0.3	-2E-5	-7E-6	-6E-6	-6E-6	-6E-6	-6E-6	-6E-6	-6E-6	-6E-6	-6E-6	-6E-6	-2E-5	-2E-5	-2E-5	-4E-5	-7E-8
0.4	-3E-6	-1E-5	-3E-6	-3E-6	-3E-6	-3E-6	-3E-6	-3E-6	-3E-6	-3E-6	-3E-6	-3E-6	-3E-6	-3E-6	-2E-4	-7E-6
0.5	-1E-6	-8E-6	-1E-5	-3E-6	-2E-8	-4E-6	-4E-6	-4E-6	-4E-6	-4E-6	-1E-6	-1E-6	-1E-6	-1E-6	-1E-8	-5E-6
0.6	-5E-7	-1E-5	-4E-6	-1E-5	-1E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-5E-7	-5E-7	-5E-7	-2E-7	-1E-5
0.7	-8E-7	-2E-5	-6E-7	-1E-5	-2E-5	-1E-5	-1E-5	-1E-5	-1E-5	-1E-5	-1E-6	-8E-7	-8E-7	-8E-7	-1E-8	-1E-5
0.8	-9E-7	-2E-5	-2E-5	-2E-5	-2E-5	-3E-6	-3E-6	-3E-6	-3E-6	-3E-6	-2E-5	-9E-7	-9E-7	-9E-7	-5E-9	-6E-6
0.9	-4E-6	-3E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-4E-6	-4E-6	-4E-6	-6E-5	-3E-6
1.0	-1E-7	-3E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-2E-5	-1E-7	-1E-7	-1E-7	-3E-8	-1E-6

Table 3. The number of stable instances with a closed loop for 16 scheduling methods.

α	ToB(α)											EP	ES	SEPT	LEPT	FCFS
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0					
0.0	116	0	0	0	0	0	0	0	0	0	0	116	116	116	51	42
0.1	140	54	41	40	40	40	40	40	40	40	35	140	140	140	23	125
0.2	138	50	32	31	27	29	29	29	29	29	20	138	138	138	66	123
0.3	136	51	29	23	20	15	15	15	15	15	20	136	136	136	53	112
0.4	140	88	84	86	77	70	70	70	70	70	68	140	140	140	34	118
0.5	136	108	105	103	100	106	106	106	106	106	103	136	136	136	16	131
0.6	138	97	104	104	101	100	100	100	100	100	95	138	138	138	20	137
0.7	143	105	97	99	99	98	98	98	98	98	101	143	143	143	13	138
0.8	143	109	106	106	105	105	105	105	105	105	103	143	143	143	7	142
0.9	144	111	104	105	104	101	101	101	101	101	103	144	144	144	7	138
1.0	144	121	107	105	103	101	101	101	101	101	103	144	144	144	6	141

Table 4. Gain margins of closed-loop transfer functions for 16 scheduling methods.

α		ToB(α)											EP	ES	SEPT	LEPT	FCFS
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0					
	Max	0.96	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.96	0.96	0.96	0.87	0.89
0.0	Min	0.00	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
	Avg	0.17	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.17	0.17	0.17	0.17	0.36
	Max	9.90	0.30	0.31	0.31	0.32	0.30	0.30	0.30	0.30	0.30	0.29	9.90	9.90	9.90	0.71	1.00
0.1	Min	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	0.00	0.00	0.00
	Avg	0.18	0.06	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.03	0.18	0.18	0.18	0.12	0.09
	Max	0.39	0.99	0.98	1.00	0.99	0.98	0.98	0.98	0.98	0.98	1.00	0.39	0.39	0.39	0.29	0.83
0.2	Min	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	0.00	0.00	0.00
	Avg	0.02	0.28	0.19	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.02	0.02	0.02	0.11	0.15
	Max	67.20	0.99	1.00	0.88	1.00	0.89	0.89	0.89	0.89	0.89	0.88	67.20	67.20	67.20	0.74	0.97
0.3	Min	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	0.00	0.00	0.00
	Avg	1.03	0.28	0.24	0.24	0.24	0.23	0.23	0.23	0.23	0.23	0.24	1.03	1.03	1.03	0.10	0.24
	Max	25.12	1.00	0.97	0.96	0.95	0.96	0.96	0.96	0.96	0.96	0.97	25.12	25.12	25.12	0.73	0.97
0.4	Min	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	0.00	0.00	0.00
	Avg	0.33	0.34	0.34	0.33	0.32	0.31	0.31	0.31	0.31	0.31	0.32	0.33	0.33	0.33	0.10	0.25
	Max	37.09	0.93	1.00	0.99	0.97	0.93	0.93	0.93	0.93	0.93	0.96	37.09	37.09	37.09	0.98	0.99
0.5	Min	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	0.00	0.00	0.00
	Avg	0.65	0.34	0.35	0.35	0.35	0.37	0.37	0.37	0.37	0.37	0.37	0.65	0.65	0.65	0.13	0.24
	Max	32.48	0.98	0.91	0.97	0.97	1.00	1.00	1.00	1.00	1.00	0.98	32.48	32.48	32.48	0.81	18.50
0.6	Min	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	0.00	0.00	0.00
	Avg	0.57	0.29	0.30	0.32	0.32	0.34	0.34	0.34	0.34	0.34	0.34	0.57	0.57	0.57	0.19	0.36
	Max	45.05	0.97	0.99	0.99	1.00	0.99	0.99	0.99	0.99	0.99	0.98	45.05	45.05	45.05	0.94	20.74
0.7	Min	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	0.00	0.00	0.00
	Avg	0.41	0.28	0.29	0.29	0.30	0.30	0.30	0.30	0.30	0.30	0.31	0.41	0.41	0.41	0.22	0.38
	Max	0.43	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.43	0.43	0.43	0.75	0.77
0.8	Min	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	0.00	0.00	0.00
	Avg	0.02	0.28	0.27	0.26	0.27	0.26	0.26	0.26	0.26	0.26	0.28	0.02	0.02	0.02	0.25	0.18
	Max	8.20	0.99	0.98	1.00	0.97	0.95	0.95	0.95	0.95	0.95	0.99	8.20	8.20	8.20	0.85	62.47
0.9	Min	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	0.00	0.02	0.00
	Avg	0.08	0.31	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.08	0.08	0.08	0.27	0.70
	Max	97.92	0.98	0.99	1.00	1.00	0.97	0.97	0.97	0.97	0.97	0.95	97.92	97.92	97.92	0.77	0.87
1.0	Min	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	0.00	0.00	0.00
	Avg	2.35	0.30	0.28	0.27	0.27	0.28	0.28	0.28	0.28	0.28	0.30	2.35	2.35	2.35	0.31	0.16

Table 5. Phase margins of closed-loop transfer functions for 16 scheduling methods.

α		ToB(α)											EP	ES	SEPT	LEPT	FCFS
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0					
0.0	Max	96.75	98.95	99.44	99.35	99.29	99.55	99.55	99.55	99.55	99.55	99.55	96.75	96.75	96.75	95.10	98.59
	Min	4.57	10.21	15.23	13.27	17.60	15.04	15.04	15.04	15.04	15.04	10.43	4.57	4.57	4.57	3.36	0.11
	Avg	73.45	47.60	47.55	47.85	48.35	48.07	48.07	48.07	48.07	48.07	48.49	73.45	73.45	73.45	76.88	32.79
0.1	Max	98.79	76.79	75.19	74.69	73.99	72.02	72.02	72.02	72.02	72.02	73.19	98.79	98.79	98.79	91.26	97.34
	Min	10.57	0.04	0.76	0.05	0.29	0.89	0.89	0.89	0.89	0.89	0.38	10.57	10.57	10.57	0.06	1.10
	Avg	84.27	30.78	33.17	33.05	33.76	33.56	33.56	33.56	33.56	33.56	33.15	84.27	84.27	84.27	28.64	47.85
0.2	Max	99.73	97.13	96.32	96.84	97.06	96.97	96.97	96.97	96.97	96.97	96.99	99.73	99.73	99.73	81.74	98.93
	Min	14.82	0.31	2.02	0.77	0.45	0.21	0.21	0.21	0.21	0.21	0.07	14.82	14.82	14.82	0.41	0.20
	Avg	82.20	43.49	44.96	44.69	45.24	44.66	44.66	44.66	44.66	44.66	44.28	82.20	82.20	82.20	30.85	54.40
0.3	Max	97.82	98.17	94.67	94.67	94.63	94.58	94.58	94.58	94.58	94.58	94.53	97.82	97.82	97.82	97.10	98.53
	Min	11.24	0.21	0.56	1.07	0.36	0.40	0.40	0.40	0.40	0.40	0.19	11.24	11.24	11.24	0.17	1.77
	Avg	77.77	52.58	51.90	53.13	50.06	49.80	49.80	49.80	49.80	49.80	50.39	77.77	77.77	77.77	38.93	57.17
0.4	Max	98.76	99.45	93.61	93.68	98.26	98.47	98.47	98.47	98.47	98.47	99.82	98.76	98.76	98.76	88.41	96.75
	Min	8.74	6.40	1.05	0.08	0.80	1.44	1.44	1.44	1.44	1.44	1.88	8.74	8.74	8.74	0.32	3.98
	Avg	79.91	58.94	50.53	52.58	53.92	55.08	55.08	55.08	55.08	55.08	55.04	79.91	79.91	79.91	52.45	64.02
0.5	Max	98.26	99.13	99.43	98.24	97.29	95.39	95.39	95.39	95.39	95.39	92.78	98.26	98.26	98.26	99.63	99.38
	Min	16.12	1.34	0.04	1.92	1.47	0.99	0.99	0.99	0.99	0.99	0.94	16.12	16.12	16.12	0.34	1.89
	Avg	81.97	62.96	60.83	60.62	60.53	60.73	60.73	60.73	60.73	60.73	60.96	81.97	81.97	81.97	72.30	62.21
0.6	Max	94.47	92.31	92.42	92.05	92.39	92.20	92.20	92.20	92.20	92.20	98.50	94.47	94.47	94.47	89.33	97.94
	Min	23.83	2.90	6.64	3.17	6.98	8.50	8.50	8.50	8.50	8.50	8.30	23.83	23.83	23.83	0.42	0.31
	Avg	82.71	67.62	67.11	66.29	65.82	65.02	65.02	65.02	65.02	65.02	65.14	82.71	82.71	82.71	67.78	64.31
0.7	Max	93.26	98.00	94.72	96.68	97.62	97.17	97.17	97.17	97.17	97.17	92.09	93.26	93.26	93.26	89.26	99.34
	Min	11.62	11.29	9.27	8.46	12.89	14.39	14.39	14.39	14.39	14.39	15.71	11.62	11.62	11.62	3.38	4.52
	Avg	81.37	71.71	69.82	69.66	69.83	70.08	70.08	70.08	70.08	70.08	69.38	81.37	81.37	81.37	71.74	68.44
0.8	Max	92.75	91.65	96.63	91.83	91.85	95.44	95.44	95.44	95.44	95.44	98.70	92.75	92.75	92.75	88.48	98.03
	Min	15.90	2.37	1.33	1.88	1.59	2.16	2.16	2.16	2.16	2.16	1.16	15.90	15.90	15.90	38.98	23.58
	Avg	80.69	71.59	73.82	72.93	72.59	72.95	72.95	72.95	72.95	72.95	72.69	80.69	80.69	80.69	73.06	72.93
0.9	Max	91.87	91.46	95.84	95.57	94.87	94.94	94.94	94.94	94.94	94.94	95.00	91.87	91.87	91.87	96.22	99.64
	Min	12.33	1.47	0.22	3.40	3.54	2.26	2.26	2.26	2.26	2.26	0.23	12.33	12.33	12.33	47.04	12.59
	Avg	80.34	69.72	73.25	73.86	73.49	73.89	73.89	73.89	73.89	73.89	74.47	80.34	80.34	80.34	72.72	74.87
1.0	Max	94.27	91.34	93.98	95.47	93.34	93.60	93.60	93.60	93.60	93.60	94.58	94.27	94.27	94.27	91.35	98.99
	Min	22.80	2.95	1.46	0.93	0.72	6.59	6.59	6.59	6.59	6.59	9.06	22.80	22.80	22.80	26.33	2.23
	Avg	80.24	70.89	71.57	71.68	72.32	72.52	72.52	72.52	72.52	72.52	72.52	80.24	80.24	80.24	69.65	75.67

Table 6. Average gain margins across 5 *CV* levels of processing time uncertainties with even preferences on KPIs for 16 scheduling methods.

CV	ToB(α)											EP	ES	SEPT	LEPT	FCFS
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0					
0.1	0.29	0.40	0.41	0.41	0.43	0.43	0.43	0.43	0.43	0.43	0.45	0.12	0.72	0.29	0.29	0.16
0.2	1.56	0.36	0.38	0.39	0.39	0.41	0.41	0.41	0.41	0.41	0.40	1.29	0.51	1.56	0.30	0.17
0.3	0.62	0.34	0.35	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.39	0.55	0.54	0.62	0.40	0.14
0.4	0.38	0.34	0.42	0.37	0.35	0.37	0.37	0.37	0.37	0.37	0.43	0.35	0.23	0.38	0.47	0.40
0.5	0.29	0.30	0.56	0.33	0.35	0.33	0.33	0.33	0.33	0.33	0.35	0.16	0.74	0.29	0.58	0.52
Avg	0.63	0.35	0.43	0.37	0.38	0.38	0.38	0.38	0.38	0.38	0.40	0.49	0.55	0.63	0.41	0.28

Table 7. Average phase margins across 5 *CV* levels of processing time uncertainties with even preferences on KPIs for 16 scheduling methods.

CV	ToB(α)											EP	ES	SEPT	LEPT	FCFS
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0					
0.1	87.28	58.88	54.46	53.82	53.72	52.03	52.03	52.03	52.03	52.03	53.05	87.20	87.33	87.28	61.18	67.54
0.2	87.61	58.89	55.19	54.95	53.99	53.29	53.29	53.29	53.29	53.29	52.82	88.33	87.81	87.61	56.80	67.91
0.3	87.19	60.63	58.57	56.62	58.09	55.26	55.26	55.26	55.26	55.26	57.29	87.72	86.17	87.19	53.83	69.90
0.4	85.24	63.97	61.89	61.00	61.46	60.38	60.38	60.38	60.38	60.38	60.79	86.17	86.45	85.24	46.21	72.46
0.5	86.38	67.44	64.53	64.57	62.59	64.13	64.13	64.13	64.13	64.13	61.76	86.36	85.39	86.38	39.23	72.35
Avg	86.74	61.96	58.93	58.19	57.97	57.02	57.02	57.02	57.02	57.02	57.14	87.16	86.63	86.74	51.45	70.03

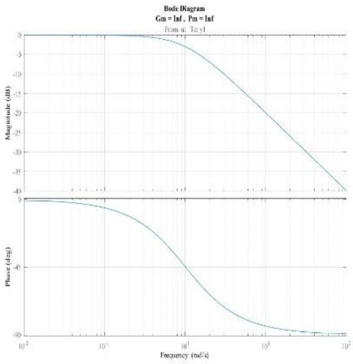

Fig 1. Gain and phase margins in a Bode plot.

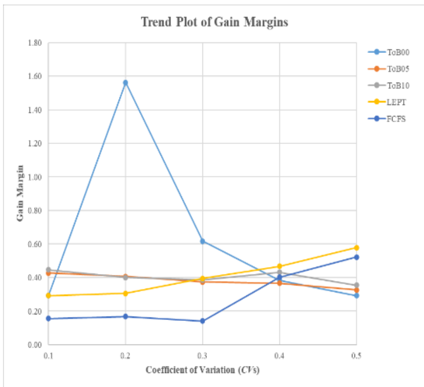

Fig. 2. Trend plot of gain margins across *CV*s.

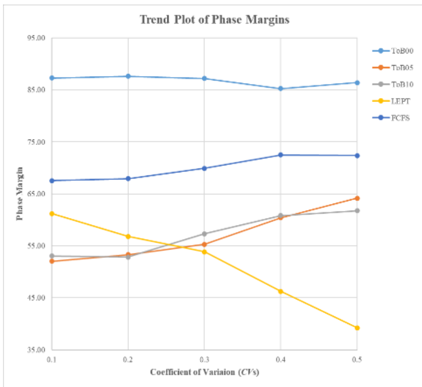

Fig. 3. Trend plot of phase margins across *CV*s.

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