Variability propagation in manufacturing systems: the impact of the processing time distribution

Graphical Abstract

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Highlights

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- In balanced and unpaced lines, the propagated variability increases with processing time skewness;
- Other affecting factors are inter-arrival and processing time variability, utilisation, line size;
- Low inter-arrival time variability and medium utilisation levels increase variability propagation;
- Longer lines propagate more variability, and processing time distribution can further amplify it;
- Industry 4.0 and 5.0 systems are more exposed to the effects of the processing time distribution.

Variability propagation in manufacturing systems: the impact of the processing time distribution

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Abstract

In manufacturing and service systems, variability deteriorates system performance by increasing cycle times, work in process, and their unpredictability. Approximation models and other tools, such as simulation and optimisation algorithms, are adopted for investigating and limiting variability propagation in multi-stage systems. Often, these approaches exploit only the mean and variance of the distributions of job arrivals and processing times, or they assume distributions with particular characteristics to define closed-form formulas. This paper investigates the conditions in which these assumptions are ineffective and the result of considering only the mean and variance of the processing time distribution. Balanced and unpaced lines modelled through Discrete Event Simulation are considered. The results show the impacts of the entire processing time distribution (beyond its mean and variance) on the inter-departure times, whose variability is also influenced by utilisation levels, line sizes, and inter-arrival and processing time variability. Flexible and reconfigurable manufacturing systems, largely adopted in Industry 4.0, are subjected to a variability propagation increasing with the skewness of the processing time distribution. In these cases, the entire processing time distribution should be considered in system performance assessment and optimisation to avoid misleading results due to significatively underestimated variability propagation.

Keywords: System variability, Variability propagation, Flow lines, Skewness, Discrete event simulation, Industry 4.0
PACS: 0000, 1111
2000 MSC: 0000, 1111

1. Introduction

Variability reduction is crucial for manufacturing and service systems to reduce inefficiencies related to variability propagation. Specifically, variability is known to increase the average cycle time (CT) (Romero-Silva et al., 2019b) and the average work in process (WIP), which, in turn, might decrease customer service level and require larger in-stage buffers (Tiacci, 2017). Moreover, in multi-stage systems, variability propagates from one stage to the other, thus negatively impacting also on throughput variability (and, hence, service predictability) (Khalil et al., 2008). Therefore, variability has become a key measure for the overall system performance (Roda and Macchi, 2019). As increasing the average throughput is a common goal for companies, addressing the throughput variance is important to improve performance (Taylor and Heragu, 1999).

Beyond variability reduction strategies, recent studies highlighted the need to investigate the variability sources and how they are intertwined with the operational performance of the systems (Romero-Silva et al., 2019b; Battesini et al., 2021). Investigating the sources of variability is particularly important for the manufacturing systems based on Industry 4.0 (I4.0) and Industry 5.0 (I5.0) paradigms. I4.0 manufacturing solutions such as Flexible Manufacturing Systems and Reconfigurable Manufacturing Systems allow dealing with mass customization by increasing product variety, and frequent market demand fluctuations (Yadav and Jayswal, 2018; Bortolini et al., 2018). Therefore, these types of systems are particularly exposed to variability effects.

In this context, I5.0 aims at simultaneously maximizing economic, environmental, and social profit through flexibility and reconfigurability centred on human skills and creativity (Xu et al., 2021; Maddikunta et al., 2022), and an increased decision-making role of the robots (Lu et al., 2022). Therefore, understanding the causes of the variability and its propagation is relevant because it can lead to workers' injuries and stress and eventually reduce the overall workers' performance (Malik et al., 2021).

In I4.0 and I5.0 contexts, the use of data to improve process synchronization (Felsberger et al., 2022), anomaly detection (Kuo et al., 2021), and dynamic task allocation or re-allocation (Zanchettin, 2022) might allow having a more accurate estimate of system variability and, hence, more effective use of planning tools (e.g., simulation, optimisation, and approximation models and algorithms).

However, approximation models and simulation-optimisation algorithms used in production planning often focus only on the mean and the variance of inter-arrival and processing time distributions. This is mainly due to two elements: (i) usually the single manufacturing process has small variability (Inman, 1999) and (ii) manufacturing lines are usually designed to work with a little product variety and utilisation close to 100% (Chen and Yao, 2001). However, these assumptions become weaker in the I4.0 and I5.0 paradigms because these systems need to be more flexible and more easily reconfigurable to meet demand fluctuations (Morgan et al., 2021) by requiring larger installed capacity, long transient, and frequent setups (i.e., utilisation can no longer be close to 100%)(Wang et al., 2021). Moreover, the context is usually a multi-product one (i.e., single-product dedicated lines are no longer adopted), which increases processing time variability (Curry and Feldman, 2010). In these cases, still assuming small variability and high utilisation can lead to errors larger than 10% (Tarasov, 2016; Gross and Juttijudata, 1997).

This paper investigates whether the processing time distribution shape (beyond mean and variance) affects the variability of a line under different assumptions of utilisation, system size, and inter-arrival time variability. The effects are measured at the end of the line, that is, on the inter-departure time distribution. From the numerical results, insights are discussed to support strategies that allow for reducing variability, especially in contexts adopting the new industrial paradigms.

The remainder of the paper is organised as follows. The related literature is reviewed in Section 2. Section 3 presents the study methodology and the design of experiment. Results are presented in Section 4 and discussed in Section 5. Section 6 concludes the paper.

2. Literature review

In the literature regarding the performance evaluation and optimisation of manufacturing and service systems in stochastic environments, the stochasticity of the input parameters (e.g., inter-arrival and processing times) is usually addressed by only considering the mean and the variance, instead of the complete distribution. The main reason is the possibility of tackling complex problems with a limited amount of resources. For example, two-moment approximation models require smaller samples than more complex models with higher order moments (Gross and Juttijudata, 1997). Furthermore, approximating stochastic parameters with simple distributions (such as Exponential) allows obtaining closed-form formulas for estimating system performance indicators, such as the queue length (WIP) and the waiting time (CTq), to deal with real contexts in the presence of little available data, and to address complex problems (Coito et al., 2022).

In queuing theory, using only mean and variance is based on the assumption of system utilisation close to 100% (the so-called heavy traffic condition) (Wu et al., 2018). Some studies showed that two-moment approximation models are sufficiently reliable when the squared coefficients of variation (SCV) of inter-arrival and processing time distributions are lower than one (Shanthikumar and Buzacott, 1980) so that also the skewness has a negligible impact (Myskja, 1990). These approximation models are useful to identify the upper bounds of the performance indicators (Gross and Juttijudata, 1997) and to explain most of the variability of system performance measures such as the throughput (TH) (Tan, 1998) and the WIP (Johnson and Taaffe, 1991b).

However, some studies in the field of queuing theory found that the shape of inter-arrival and processing time distributions has a non-negligible effect on the variability when single-stage approximation models are considered. Specifically, the impact of the skewness is strictly related to both utilisation and coefficients of variation of inter-arrival and processing time distributions (Johnson, 1993).

Although the magnitude of the impact on system variability of both the inter-arrival and processing time distribution shapes depends on utilisation and coefficients of variations, they seem to have different effects on system variability. In particular, the inter-arrival skewness influences both the mean and the variance of CTq, while the processing time skewness influences only the variance of the CTq (Sahin and Perrakis, 1976).

Wu et al. (2018) compared several two-moment approximations with a three-moment approximation model for the average CTq in a single server system with general distributions for both inter-arrival and processing times. They showed that, in the approximation models, the skewness has an impact when the coefficient of variation of the inter-arrival time distribution is larger than 1, regardless of the value of the coefficient of variation of the processing time distribution.

Brandwajn and Begin (2009) observed that, in single server systems with Exponential inter-arrival times and general distribution for the processing times, the average WIP increases when the coefficient of variation and the skewness of the processing time distribution increase. Instead, Johnson and

Taaffe (1991a) graphically showed, through a three-moment approximation model for a system single-stage with parallel machines, general distribution for inter-arrival times and exponentially distributed processing times, that the skewness of the inter-arrival time distribution becomes relevant when its CV increases.

All the papers just cited consider the effect of the skewness on single-stage systems while few papers studied the effects of the inter-arrival and processing time distribution shape on the variability in multi-stage systems. Hendricks and McClain (1993) investigated the inter-departure time of a manufacturing line under different conditions, and they show that the inter-departure time distribution has some relationships with the line size and the processing time skewness. In particular, the processing time skewness can be considered a predictor of the output variability, and the mean inter-departure time is slightly lower with low skewness.

Powell and Pyke (1994) investigated two-moment approximation models for production lines through a simulation approach, and they noticed that neglecting skewness and kurtosis (the fourth-order moment) led to approximation errors up to 20%. Kurtosis seems to amplify the skewness impact on TH variability. Also, the longer the lines, the more they are exposed to processing time distribution shape effects on variability although an upper bound seems to exist. However, as Powell and Pyke (1994) noted, estimating the impact of skewness and kurtosis is quite difficult, as they are largely influenced by small numerical variations, which also affects the sensitivity to outliers.

These insights fostered further empirical studies, based on simulation, to analyse the effects of the inter-arrival and processing time distributions on variability. To the best of the authors' knowledge, only three papers specifically focused on skewness impacts, and they paved the way for this research.

LAUf and Martin (1987) studied the effects of skewness and kurtosis on unpaced lines and observed that high-order moments, under certain conditions, can influence variability levels up to 5%. They showed that the lower the processing time distribution skewness, the higher the utilisation, while kurtosis seems to lead to more complex patterns but with a marginal impact. Furthermore, they observed correlated effects between line size, skewness, and kurtosis.

Romero-Silva et al. (2019a) explicitly investigated the effects of skewness on throughput variability in single-stage systems. They also found impacts for low CVs (i.e., CV ≤ 0.75, Hopp and Spearman (2008)) and observed that the CV of the inter-departure time distribution is reduced when the skewness of the inter-arrival time distribution is positive and that of processing time is negative. A further study, however, showed that the opposite skewness combination reduced both the average CTq and the WIP (Romero-Silva et al., 2020). Also, the interaction between the skewness of inter-arrival and processing time distributions seems to change with different CV values.

Although the impact on the system variability of the inter-arrival and processing time distribution shapes has been shown in the literature, a comprehensive investigation of the role of the processing time distribution shape is missing so far. There is still the need to further investigate the interactions between different levels of CV of inter-arrival and processing time distributions, line size, and system utilisation.

2.1. Contribution

This paper investigates the impact of processing time distribution shape on the mean and the variance of the inter-departure time of balanced lines. The objective is to assess how the processing time distribution shape affects the variability of such systems. The conditions that are relevant for manufacturing systems under the new industrial paradigms of I4.0 and I5.0 are explicitly considered in the paper. Specifically, it considers several combinations of the inter-arrival time SCV (influenced by fluctuating demand), processing time SCV and utilisation level (influenced by system requirements of flexibility and reconfigurability), and line size.

While recent studies specifically focused on the skewness impacts on single-stage systems (Romero-Silva et al., 2019a, 2020) and the older ones on unpaced balanced lines (LAUf and Martin, 1987), this paper addresses short, medium, and long balanced flow lines. Also, differently from some previous works that assessed the impacts of the skewness and kurtosis by using different distributions (Hendricks and McClain, 1993), this paper explicitly focuses on varying the asymmetry of the same distribution shape to isolate its effect.

3. Methodology

The impact of the processing time distribution on the mean and variance of the inter-departure time is assessed using Discrete Event Simulation. The experiment considers several combinations of utilisation rate, line size, and SCV of both the inter-arrival time and processing time distributions. Simulation is a tool largely adopted in the literature to deal with variability propagation as the analytical investigation of such issue is complex for distributions other than Exponential and Normal, and when several impacting factors are considered (Romero-Silva et al., 2019a, 2020).

3.1. Assumptions and performance measures

In this paper, the impact of processing time distributions on the variability propagation is assessed by observing the SCV of the inter-departure time at the last stage of the line:

$$SCV_{d,n} = \frac{\sigma_{d,n}^2}{\mu_{d,n}^2}, \tag{1}$$

where $\mu_{d,n}$ and $\sigma_{d,n}$ are the mean and the standard deviation, respectively, of the inter-departure time distribution d at the last stage n. In the experiment, the lines are assumed to be balanced (i.e., each stage has the same average processing time μ_p) and all the stages have the same probability distribution. Buffers at each stage are assumed to have infinite capacity. Also, the average inter-arrival time is assumed to be larger than the average processing times to have a stable system.

3.2. Inter-arrival and processing time distributions

In the literature, inter-arrival times are usually modelled by using an Exponential distribution (due to its memory-less property) (Vaughan, 2008). Instead, processing times are sometimes modelled by Exponential distributions; however, they are often modelled by Log-normal distributions Hillier (2013); Sabuncuoglu et al. (2002), to include specific characteristics such as human server processing time (Slack, 2015), unexpected failures Rodriguez and de Souza (2010); Vineyard et al. (1999), and setup between different products (Robb and Silver, 1993). In the following, the same reasoning has been used and, then, inter-arrival times will be modelled by exponentially shaped distributions, and processing times by exponentially shaped and Log-normal distributions. The aim is to assess the impact of such different shapes on the system variability.

The shape of a probability distribution is described by its moments, and the most important are: mean, variance, skewness, and kurtosis. However, in many cases, some moments can hardly be independently controlled as they are intertwined with each other. Specifically, the Exponential distribution has fixed SCV, skewness, and kurtosis ($SCV = 1$, $\tilde{\mu}_3 = 2$, and $kurt = 6$). In this paper, to overcome the impossibility of changing these parameter values, the Beta distribution is used, whose parameters can be set to obtain a distribution shape similar to the Exponential one, whose moments can be changed in the design of the experiment. Specifically, the Beta distribution has four parameters: α and β control the shape, and a and b control the support. Varying a and b keeps the distribution shape while changing the mean and variance. Figure 1 shows an Exponential distribution (in blue) and two Beta distributions with different parameter values (in green and red). The two Beta distributions have the same μ, $\tilde{\mu}_3$, and $kurt$ of the Exponential distribution but different σ^2, leading to $SCV = 0.67$ for the green Beta distribution and $SCV = 0.33$ for the red one.

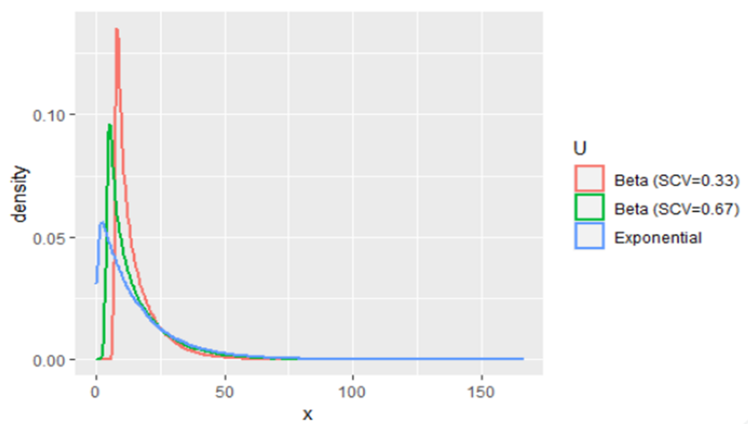

Figure 1: Exponential distribution with mean=1.5 (blue) and two Beta with the same mean, skewness, and kurtosis of the Exponential distribution but SCV=0.67, and 0.33 (in green and in red, respectively).

Instead, in the Log-normal distribution, the skewness, and the kurtosis are proportional to the standard deviation, and they increase as σ_p increases.

In this paper, the impact of the processing time distribution shape on the inter-departure time variability is assessed by comparing the $SCV_{d,n}$ of systems in which different distributions are used to model stage processing time (p), but with the same distribution for the inter-arrival time (a). Specifically, two systems are compared. Both systems have the same Beta inter-arrival distribution (with the same moments), but different distributions of processing times: one system has Beta and the other has Log-normal processing time distributions. These two processing time distributions have the same mean and variance, but different skewness and kurtosis, and the skewness and kurtosis of the Lognormal distribution are larger than those of the Beta distribution. Moreover, the α and β parameters of all the involved Beta distributions approximate an Exponential distribution that has skewness and kurtosis fixed and independent from mean and variance. Therefore, it is possible to vary the mean and variance of Beta distribution keeping fixed the distribution asymmetry to exploit it as a benchmark in the comparison with the system with Log-normal distributed processing time. As a consequence, by the comparison of these two systems, the impact of having larger skewness and kurtosis can be assessed.

3.3. Design of experiment

The experiment involves the following five factors:

- the inter-arrival time variability measured through the SCV_a (three levels: 0.33, 0.67, and 0.99);
- the processing time variability measured through the SCV_p (three levels: 0.33, 0.67, and 0.99);
- the stage utilisation u (ten levels: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 0.95);
- the processing time distribution *type* (two levels: Beta exponentially shaped *Exp* and Log-normal *Log*);
- the line size n (three levels: 3, 7, and 17);

The full factorial experiment consists of 540 different instances.

In all the instances, the mean processing time μ_p is set to 1.5. As the utilisation depends on μ_p and on the mean inter-arrival time μ_a, the values of μ_a are set to obtain the ten levels of u. For each instance, the values of the standard deviations of the inter-arrival distribution (σ_a) and of the processing time (σ_p) are set to obtain the level of SCV_a and SCV_p, respectively. For example, if $\mu_a = 15$, the three σ_a values are 8.62, 12.28, and 14.92 to obtain SCV_a levels equal 0.33, 0.67, and 0.99, respectively.

Skewness $\tilde{\mu}_{3,p}$ and kurtosis $kurt_p$ are fixed and depend on the distribution shape ($type = Exp$ or $type = Log$) and, in the case of $type = Log$, on the value of σ_p. Table A1 of the electronic companion shows the values of the first four moments of the inter-arrival and processing time distributions of each instance of the experiment.

4. Results

The initial analysis focuses on the impact of the experimental factors on the variability of the inter-departure times at the end of the n-stage line, $SCV_{d,n}$, called *response* in the following. The effect of every single factor on the response is investigated through the one-way analysis of variance (ANOVA). Then, the two-way ANOVA looks into the pairwise factor interactions to evaluate whether compensation effects might influence the results. Finally, statistical tests are performed to investigate the differences between both the means and the standard deviations of the processing time distributions of the two system types, to identify when the line size and the processing time distribution have an effect on variability.

Figure 2 shows the factor main effects on the $SCV_{d,n}$ through the one-way ANOVA. The variability of processing times SCV_p has the largest impact on $SCV_{d,n}$. Therefore, the $SCV_{d,n}$ increases with SCV_p, while the other factors show a smaller impact. The inter-arrival time variability SCV_a covers the second largest influence on $SCV_{d,n}$, followed by the utilisation u, and, finally, the system size n and the distribution *type*. The utilisation u does not have a monotonous impact on line variability; in fact, it amplifies variability when increasing from 0.1 to 0.5, while it dampens it when it increases over 0.5.

The two-way ANOVA in Figure 3 highlights the effects of the pairwise factor interactions on $SCV_{d,n}$. In each graph, the different colours represent the levels of the factor in the row while the markers represent the levels of the factor in the column. For example, the first picture on the top left represents the interactions among the SCV_a levels (0.33, 0.67, and 0.99) and the ten levels of u (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95). The right vertical axis indicates the values of $SCV_{d,n}$.

The top-left graph in Figure 3 shows that the SCV_a levels (green, red, and blue lines), which are the second main effect in Figure 2, have a different impact on $SCV_{d,n}$ only for low u levels (overlapping markers). The SCV_a levels have an impact on $SCV_{d,n}$ also when considered together with other factors (green, red, and blue lines are not overlapping in graphs SCV_a-SCV_p, SCV_a-n, and SCV_a-*type*). Specifically, there is a monotonous and constant interaction between SCV_a-SCV_p levels (parallel lines with non-negligible slope in picture SCV_a-SCV_p), weak interaction between SCV_a-*type* (parallel lines

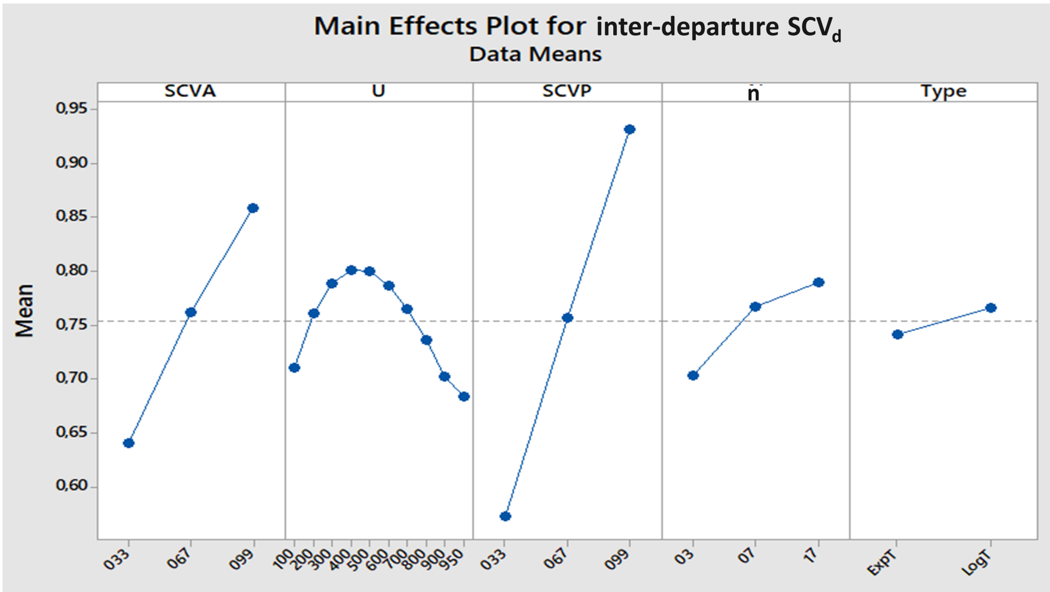

Figure 2: Main effects plot of inter-arrival time variability, stage utilisation, processing time variability, number of stages, and distribution types, on the squared coefficient of variation of the inter-departure time from the last stage.

with small slope in SCV_a-$type$), and an inverse interaction with SCV_a-n levels (in picture SCV_a-n, the value of $SCV_{d,n}$ decreases for high SCV_a and increasing n, and it increases for low SCV_a and increasing n).

The n levels present an inverse interaction with SCV_a and SCV_p, while only medium and large n sizes seem to be influenced by *type* (red and green lines overlapping and with a steeper slope with respect to the blue line in the n-$type$ graph). Furthermore, the longer the system, the greater the impact of u. Conversely, the overall impact of *type*, that is, the impact of increasing skewness and kurtosis ($\tilde{\mu}_3 = 2$ and $kurt = 6$ for $type = Exp$, $\tilde{\mu}_3 = 2, 3, 4$ and $kurt = 7, 19, 37$ for $type = Log$ and increasing σ_p) seems weak or null. In particular, *type* seems weakly influenced by SCV_a levels, and only influenced by high SCV_p and long lines. However, the interactions between SCV_a-n, which are opposite with respect to SCV_a-$type$, and the interactions between SCV_p-n and SCV_p-$type$, which may amplify the interactions n-$type$, suggest further analyses to deepen the overall impact of *type*. In fact, the two-way ANOVA cannot capture the interactions among more than two factors, and its results may be affected by compensation effects.

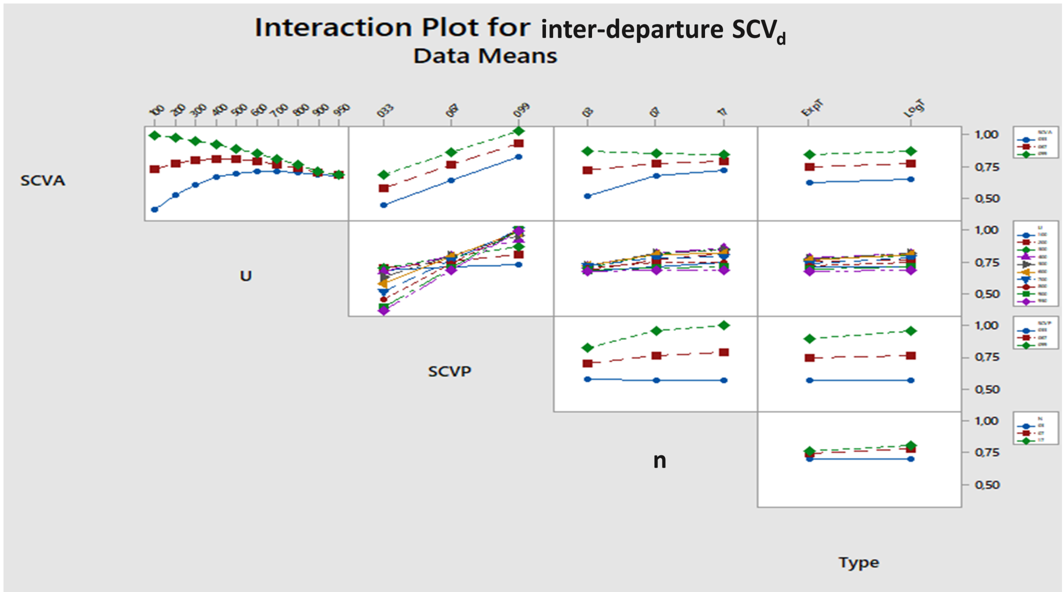

Figure 3: Pairwise factor interaction impacts on $SCV_{d,n}$ (vertical axis on the right).

The effects of *type* and its interactions with n are deepened by focusing first on the line size and then on the distribution. The analysis on line size aims at highlighting whether the *type* affects in different ways the impacts of n on variability propagation by amplifying or dampening it. Successively, the analysis on *type* investigates the overall impact of the processing time distribution shape on variability propagation when the experimental factors vary.

4.1. The impact of the system size

As seen in the previous analyses, the line size impacts the $SCV_{d,n}$; however, the effects on the single $\sigma_{d,n}$ and $\mu_{d,n}$ have still to be assessed. The first step is comparing $\mu_{d,n}$ and $\sigma_{d,n}$ of instances with different line size, while SCV_a, SCV_p, u, and *type* are the same. Two comparisons are performed: (1) lines with $n = 3$ and $n = 7$; (2) lines with $n = 7$ and $n = 17$. The comparison between lines with n equal to 3 and 17 can be inferred from comparisons (1) and (2); in fact, the main effects plot of Figure 2 shows that line size has a monotonic effect on variability, and in Figure 3, the pairwise interactions plot does not highlight opposite interactions with respect to the line size.

First, the hypotheses that the means and the standard deviations are statistically different are tested, and the results are shown through the coloured grid graphs. Then, only the cases of statistically different means and standard deviations are investigated to assess the magnitude of the size impact.

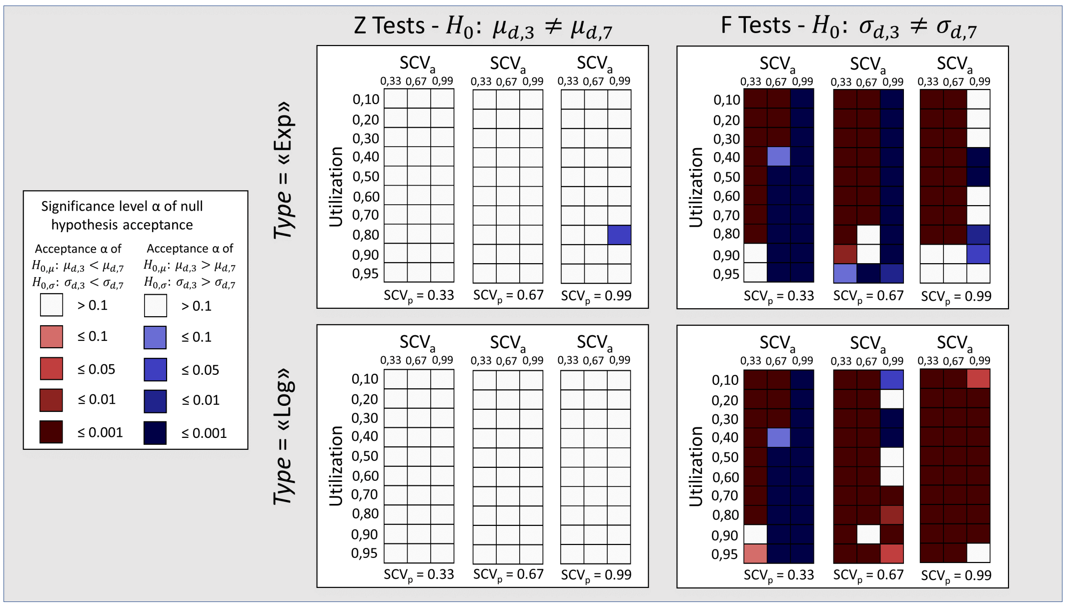

Figure 4: Hypothesis tests for the differences between the means (sets on the left) and between the variances (sets on the right) when $type = Exp$ (sets on the top) and $type = Log$ (sets on the bottom), for $n = 3$ and $n = 7$.

Figures 4 and 5 show the minimum significance level α with which the null hypothesis (e.g., $H_{0,\mu} : \mu_{d,3} \geq \mu_{d,7}$ or $H_{0,\mu} : \mu_{d,3} \leq \mu_{d,7}$) cannot be rejected, for each combination of factors, for the mean and the standard deviation of the lines in comparisons (1) and (2). In particular, in each figure, there are four sets of three grids. The two sets on the top are related to the test for the differences in the means (the set on the left) and the standard deviations (the set on the right) when $type = Exp$. Conversely, the two sets on the bottom show the tests for means and standard deviations when $type = Log$. In each set, the three vertical grids represent SCV_p levels (increasing SCV_p from left to right). In each grid, the three columns represent the three SCV_a levels, increasing from left to right. The ten rows in each grid identify the u levels, increasing from top to bottom. The squares are white when the means or the standard deviations cannot be considered statistically different. Conversely,

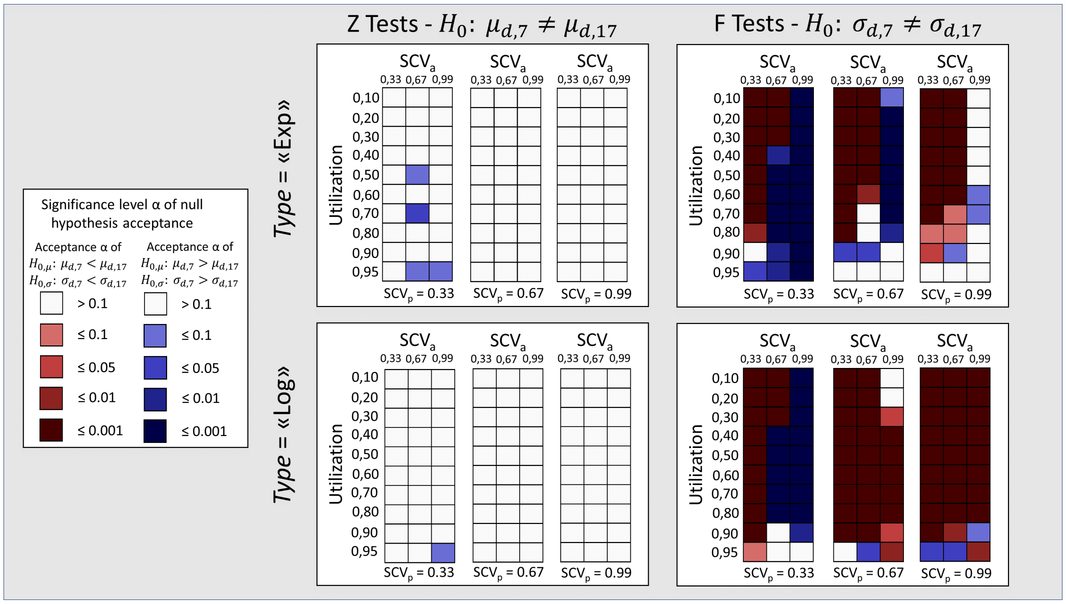

Figure 5: Hypothesis tests for the differences between the means (sets on the left) and between the variances (sets on the right) when *type* = *Exp* (sets on the top) and *type* = *Log* (sets on the bottom), for $n = 7$ and $n = 17$.

they have darker shades of red when the means or the standard deviation of the first member of the test is lower than the second, and darker shades of blue when the second is lower than the first.

Figure 4 shows that the mean of the inter-departure time is never affected by the line size except for the case of $type = Exp$, $SCV_a = 0.99$, $SCV_p = 0.99$, and $u = 0.8$, in which the blue colour indicates that, with an acceptance α level lower than 0.05, $\mu_{d,3} \geq \mu_{d,7}$. Conversely, the standard deviation of the inter-departure times is affected by both the line size and its interactions with processing time *type*.

However, the size effect on the standard deviation is not constant, and there is a turning point that shows how the effect changes. The shorter lines propagate less variability than the longer ones for small values of SCV_a (the first columns of the coloured grids). When SCV_a increases, the behaviour is reversed (blue squares replace the red ones). The turning point depends on SCV_p and u; specifically, the larger the SCV_p, the larger the u values corresponding to the turning point. For example, in Figure 4 for $type = Exp$ and $SCV_p = 0.33$, the turning point is for $SCV_a = 0.67$ and $u = 0.4$; when

$SCV_p = 0.67$, the turning point is for $SCV_a = 0.67$ and $u = 0.95$.

For $type = Exp$, when SCV_a and SCV_p are large, the difference between standard deviations of shorter and longer lines becomes less significant (increase in the number of white squares in the boxes in the middle and on the right).

Figure 5 shows that the differences between $n = 7$ and $n = 3$ are similar to those between $n = 17$ and $n = 7$ with the exception of slightly lower differences when u is large, $type = Exp$, and $SCV_p = 0.99$. Therefore, the impact of line size on variability propagation is monotonously increasing with the number of stages.

The magnitude of the impacts of the differences between the standard deviations on $SCV_{d,n}$ is shown in Figure 6. Figure 6 reports nine bar charts in which SCV_p increases from left to right from 0.33 to 0.99, and SCV_a increases from the top to the bottom from 0.33 to 0.99. Each bar chart shows four bars, one for each of the following indicators:

- $GAP_{3,7,Exp} = \frac{SCV_{d,3} - SCV_{d,7}}{SCV_{d,7}}$ when $type = Exp$ (blue bars);
- $GAP_{3,7,Log} = \frac{SCV_{d,3} - SCV_{d,7}}{SCV_{d,7}}$ when $type = Log$ (orange bars);
- $GAP_{7,17,Exp} = \frac{SCV_{d,7} - SCV_{d,17}}{SCV_{d,17}}$ when $type = Exp$ (gray bars);
- $GAP_{7,17,Log} = \frac{SCV_{d,7} - SCV_{d,17}}{SCV_{d,17}}$ when $type = Log$ (yellow bars);

Bars with positive height in Figure 6 are related to the blue squares of Figures 4 and 5, that is, the shorter the line, the higher the propagated variability in terms of SCV_d (considering that coloured grid charts showed no differences among μ_d and statistically significant differences among σ_d). Conversely, bars with negative height are related to the red squares, that is, the shorter the line, the lower the propagated variability. The turning points identified in Figures 4 and 5 are here represented by the changes in bar orientations from negative to positive.

On the one hand, when SCV_a increases, the variability propagated by the longer lines is reduced (this can be appreciated by comparing the graphs from the top to the bottom of Figure 6). On the other hand, when SCV_p increases (i.e., when moving from the graphs on the left to those on the right of Figure 6), the variability propagated by larger line size is amplified. Furthermore, the maximum of the variability propagated by longer lines moves from $u =$

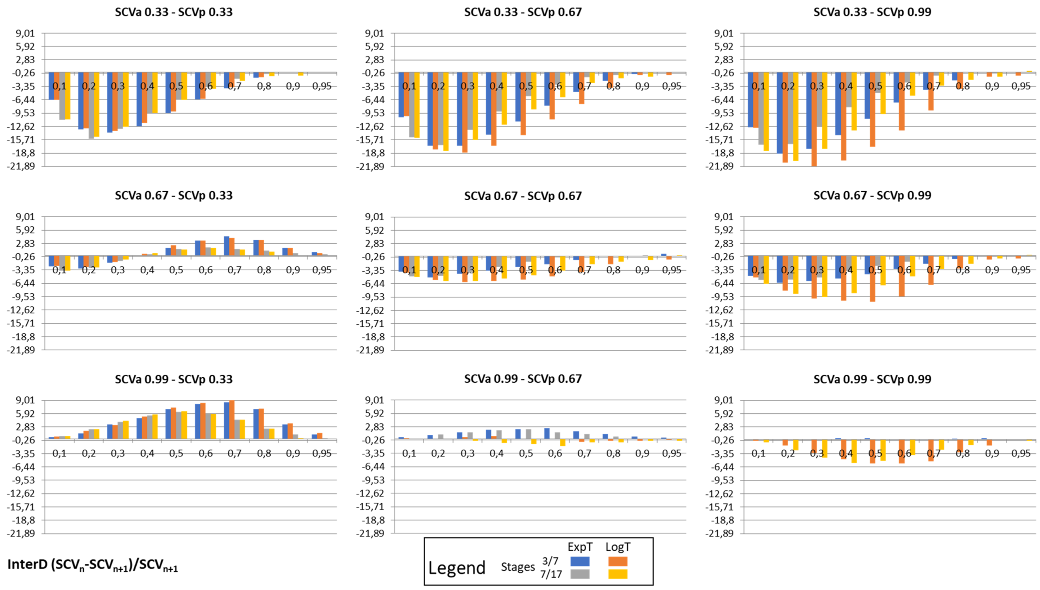

Figure 6: Bar charts for the differences of the squared coefficient of variation of inter-departure time comparing lines with 3 and 7 stages, and lines with 7 and 17 stages, with $type = Exp$ and $type = Log$.

0.3 to $u = 0.6$ when SCV_a increases (i.e., observing the graphs in Figure 6 from top to bottom, the highest bars of each graph moves from $u = 0.3$ to $u = 0.6$).

The interaction between $type = Log$ and the levels of n increases when SCV_p increases (orange and yellow bars are higher than blue and grey, respectively), thus amplifying the variability propagated by longer lines. The interaction between $type = Log$ and the levels of n is amplified by higher u, but the difference in the variability propagation due to the line size tends to 0 when u tends to 1. Finally, larger SCV_p have different impacts when comparing line sizes 3-7 and 7-17. Two main effects can be identified: the size impacts variability propagation, and it interacts with the distribution shape.

The first impact is evaluated by comparing the blue bar with the grey bar and the orange bar with the yellow bar in the bar charts for $SCV_p = 0.99$. For $u \geq 0.2$, the blue and the orange bars are shorter than the grey and the yellow ones; thus, the difference between lines with $n = 7$ and $n = 3$ is larger than that one between lines with $n = 17$ and $n = 7$; however, the longer the line, the greater the propagated variability, with no distribution shape effect. Hence, the variability propagated by the line size seems to increase, with a decreasing rate, towards an upper bound.

The second effect, that is, the interaction between line size and distribution shape, is evaluated by comparing blue and grey bars with orange and yellow bars. When $SCV_p = 0.33$ (the three bar charts in the left column), the skewness is the same (it is equal to 2 for both $type = Exp$ and $type = Log$) while the kurtosis is only similar (it is equal to 6 for $type = Exp$ and it is equal to 7 $type = Log$) and there is a negligible difference between orange and blue bars and between yellow and grey bars. However, higher SCV_p values amplify the difference of variability between shorter and longer lines; in fact, orange and yellow bars are higher than blue and grey bars even though a decreasing rate can still be observed. Hence, the more skewed the processing time distributions, the more amplified the variability propagated by the line size.

The utilisation level is important to determine the size effect on the variability propagation. In particular, for low utilisation levels, the longer the lines, the larger the difference. Instead, for medium utilisation levels, the differences in the inter-departure time variance decrease when the line sizes increase.

When both SCV_a and SCV_p proportionally increase, the experiment shows the impact on the variability of the processing time distribution asymmetrical shape. The overall line size effect decreases from $SCV_a = 0.33 - SCV_p = 0.33$ to $SCV_a = 0.99 - SCV_p = 0.99$. However, a direct amplification effect of processing time distribution asymmetry on the line size effect emerges. In fact, in $SCV_a = 0.99 - SCV_p = 0.99$, there is no line size impact on inter-departure time variability when inter-arrival and processing time distributions have the same skewness and kurtosis; while when skewness and kurtosis increase, the longer the line, the larger the inter-departure time variability.

These analyses assess the line size contribution to the inter-departure time variability and how and when the distribution shape can amplify such an effect.

4.2. The impact of the processing time distribution

The analysis done in Section 4.1 shows that the distribution shape can contribute to amplifying or dampening the propagated variability in some cases (i.e., depending on the combination of the other factors). Therefore, the overall impact of *type* is investigated by fixing all the other factors.

Figure 7 shows the coloured grid graphs for the results of the hypothesis tests for means (the three sets on the top) and variances (the three sets on the bottom). Each set includes three grids for the three levels of SCV_p, increasing from the left to the right, and each grid consists of three columns (the three SCV_a levels) and ten rows (the u levels). Each square shows the results of a hypothesis test through its colour: white if the difference is negligible, red shades when the mean or the variance of $type = Exp$ is greater than that of $type = Log$, and blue shades in the opposite case.

Also in this case, the mean inter-departure time is not influenced by the processing time distribution. Conversely, the inter-departure time variance is affected by the processing time distribution. The variability has the same trend for all three levels of n. When $SCV_p = 0.33$, the system with $type = Exp$ has a larger variance. Instead, for higher SCV_p, the system with $type = Log$ propagates greater variability except for $u = 0.1$. Differently from the previous analysis, the results of Figure 7 show that shorter lines are scarcely affected by processing time distribution for $u \leq 0.3$, while longer lines are scarcely affected for $u \leq 0.1$ and $u \geq 0.9$ when $SCV_a = 0.33$.

Figure 8 shows the magnitude of the impact of *type* on variability propagation. There are nine bar charts in which SCV_p increases from left to right moving from 0.33 to 0.99, and SCV_a increases from the top to the bottom, moving from 0.33 to 0.99. Each bar chart shows three bars, whose heights are computed as:

- $Gap_{Log,Exp,3} = \frac{SCV_{d,Log} - SCV_{d,Exp}}{SCV_{d,Exp}}$ when $n = 3$ (blue bars);
- $Gap_{Log,Exp,7} = \frac{SCV_{d,Log} - SCV_{d,Exp}}{SCV_{d,Exp}}$ when $n = 7$ (orange bars);
- $Gap_{Log,Exp,17} = \frac{SCV_{d,Log} - SCV_{d,Exp}}{SCV_{d,Exp}}$ when $n = 17$ (grey bars).

Positive bars refer to dark blue squares in Figure 7 in which the system with $type = Log$ propagated more variability than the system with $type = Exp$, while negative bars refer to dark red ones. When SCV_a increases, the difference between the lines decreases. Instead, when SCV_p increases, it amplifies the variability led by the processing time distribution shape. Moreover, the longer the line, the larger the variability difference, that is, $Gap_{Log,Exp,17}$ is larger than $Gap_{Log,Exp,7}$ (grey bars are the highest, followed by

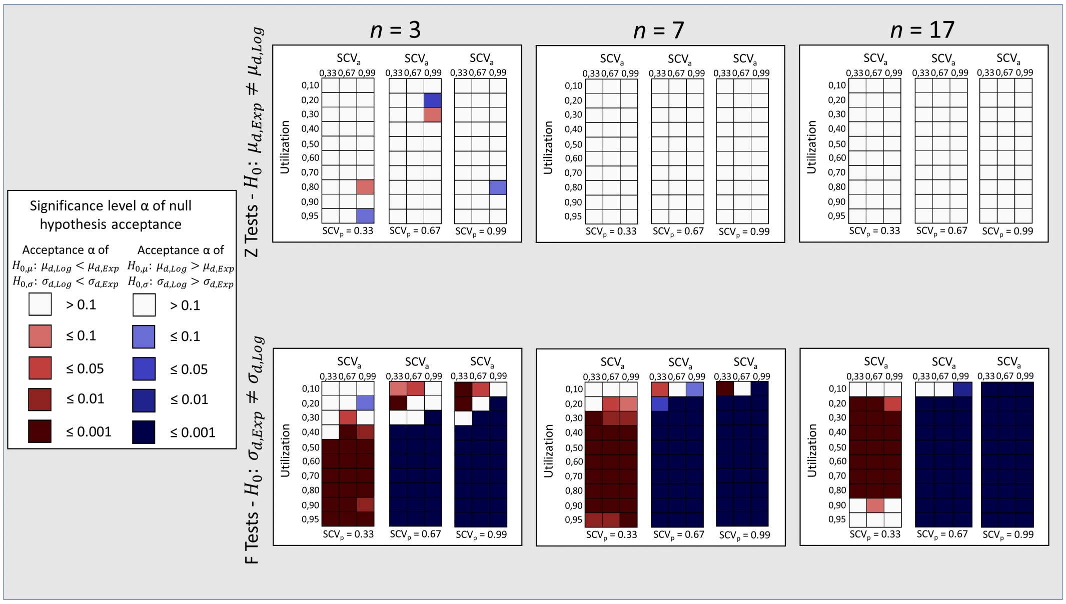

Figure 7: Hypothesis tests for the differences between the means (sets on the top) and between the variances (sets on the bottom).

the orange ones). The *type* impact increases from $u = 0.1$ to a maximum, and then it decreases until $u = 0.9$. The shorter the line, the greater the u where the maximum is achieved. For example, in $SCV_a = 0.33$ and $SCV_p = 0.99$ the peak for $n = 3$ is in $u = 0.8$, for $n = 7$ is in $u = 0.6$, and for $n = 17$ is in $u = 0.5$.

The effects of processing time distribution asymmetry can be observed in the bar charts where $SCV_a = SCV_p$ as the two compared systems (i.e., the one with exponentially shaped processing times and the other with Lognormal processing times) are equal except for skewness and kurtosis of the processing time distributions. The increasing asymmetry coupled with the increasing σ_p propagate more variability on the inter-departure times than the system with constant asymmetry of the processing time distribution.

The differences in the propagated variability of the more skewed processing time distribution are maximum for medium utilisation levels even though it also affects higher and lower utilisation levels.

The bar chart $SCV_a = 0.33 - SCV_p = 0.33$ in Figure 6 shows the non-negligible effect of the kurtosis. In fact, the two system processing time distributions have the same mean, variance, and skewness, but the Lognormal

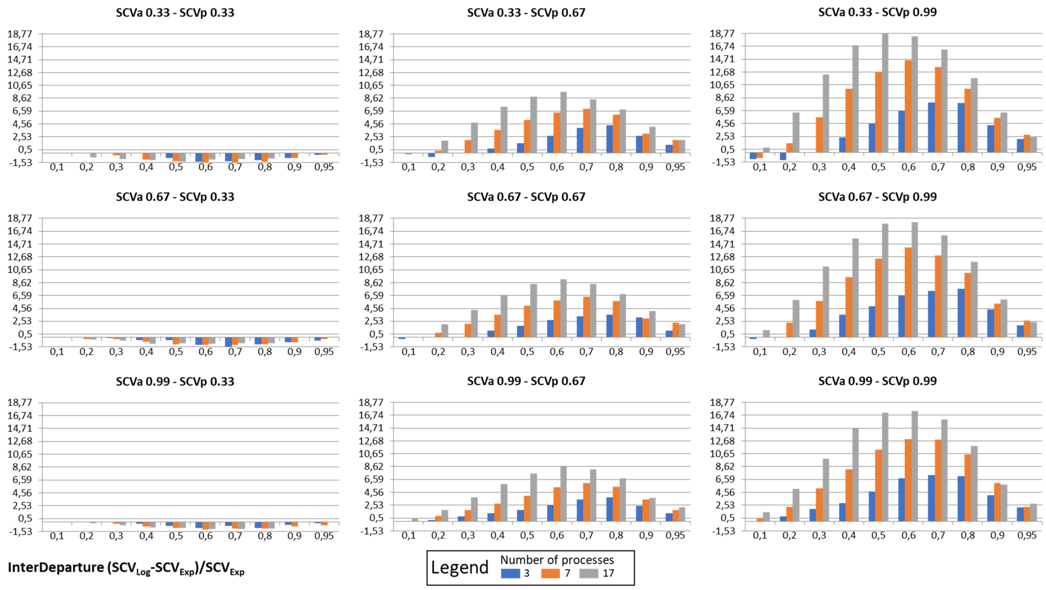

Figure 8: Bar charts for the differences of the squared coefficient of variation of inter-departure time comparing lines with $type = Exp$ and $type = Log$, for $n = 3$, $n = 7$, and $n = 17$.

distribution has a slightly larger kurtosis that increases the inter-departure time variance. It seems that larger kurtosis mitigates the propagated variability.

The increasing of SCV_a has a twofold effect on the propagated variability. It slightly reduces the difference of the propagated variability in the inter-departure times, and, according to Figure 6, it reduces the line size effect on the propagated variability even though the larger the asymmetry of the processing time distribution, the larger the propagated variability.

5. Discussion

The results show that the distribution shape has an effect on the variability propagation also for low levels of inter-arrival and processing time SCV and utilisation. The mean inter-departure time is not affected by the line size and the processing time distribution under any of the considered conditions. Instead, line size and processing time distribution shape directly influence the variance of the inter-departure time, and the larger the processing time variance and its asymmetry, the larger the propagated variability. Hence, theoretical approximation, simulation models and optimisation algorithms that neglect the distribution shape might give inaccurate results, especially for systems with medium utilisation levels.

Also, the interaction between the processing time distribution and many other factors (e.g., inter-arrival and processing time SCV, utilisation levels, and the number of stages of the system) makes the prediction of system variability difficult. In fact, the propagated variability is sensitive to changes in utilisation levels and inter-arrival and processing time SCV in a way that depends on the asymmetry of processing time distribution.

The impact of line size and processing time distribution on the variability propagation seems to suggest that the inter-departure time distribution (and then the throughput) changes stage after stage. However, the numerical results seem to suggest that an upper bound exists on the variability propagated when increasing line size in processing time skewed distributions (Powell and Pyke, 1994).

The system size and the processing time distribution have a joint effect on variability propagation. Therefore, in all the cases in which the system configuration is flexible (such as supply chain design and production scheduling in presence of workstations able to work different tasks), the approaches for system design or reconfiguration should consider the number of stages, their utilisation level, and the entire processing time distribution rather than only its mean and standard deviation.

All in all, the experimental results suggest including the processing time distribution shape in production planning algorithms by exploiting the distribution fitting and not to consider only mean and variance when utilisation levels are far from 100%.

5.1. Managerial insights

The results of this paper have a twofold objective: they highlight the impact of approximating processing times of the single stages with mean and variance, and they also quantify the negative impact on variability propagation. These findings can support production managers and process engineers in several activities, such as production planning, reconfiguration of Reconfigurable Manufacturing Systems, production monitoring, and control.

Although the rising complexity is caused by large product variety, small lot size, and outsourced maintenance activities, a deep understanding of processing time distribution is fundamental for improving the system performance as mean and variance are insufficient. A processing time distribution characterised by many processing times slightly under the average and others abundantly larger than the average requires further analyses.

Maintenance issues can cause some processing times over the average. In this case, further maintenance strategies should be investigated. For example, according to the Lean Management principles, the production rate can be fixed by a takt time slightly larger than the mean processing time to include short maintenance activities that avoid less frequent longer stops. This approach can achieve the twofold result of avoiding both small and large processing time by smoothing the production pace and concentrating processing time density around the distribution average by reducing even the variance beyond skewness.

In multi-product environments, aggregating processing times of different products in production planning and in the evaluation of the system reconfigurations can lead to a significant underestimation of variability propagation. Specifically, although different production lot can have the same processing time mean and standard deviation, the product variety within a production lot or in a system configuration can affect variability propagation and the actual system variability. Therefore, in multi-product production planning activities, production lots should have processing times as homogeneous as possible to be comparable.

Manufacturing and service systems, in the Industry 4.0 and 5.0 paradigms, are exposed to variability propagation due to under-utilisation (Prasad and Jayswal, 2019; Diaz et al., 2021), fluctuations in the demand (Abbasi and Houshmand, 2011) and in the production volumes (Kara and Kayis, 2004), which often are subjected to long transients (Chen and Shen, 2022), large processing time SCV because of different manufactured products (Arteaga and Calvo, 2021) and frequent setups, reorganization and re-skilling of the workforce (El-Khalil and Darwish, 2019). Variability propagation can be erroneously assumed intertwined only with high inter-arrival variability and stage utilisation levels. However, inter-arrival variability is poorly relevant for variability propagation caused by asymmetrical processing time distribution, while medium utilisation levels are the most affected ones. Therefore, variability propagation can be underestimated and it can cause injuries, stress, ineffective workloads, and underperformance.

Moreover, variability propagation is particularly critical for the key performance indicators of flexible and reconfigurable manufacturing systems. In fact, these systems are commonly adopted in assembly-to-order and make-to-order industries in which variability propagation is crucial to ensure order deadlines and competitive cycle times.

6. Conclusion

This paper addresses the impact of the inter-arrival and processing time distribution shapes on the variability propagated at the end of a flow line. The experimental results, which refer to balanced small, medium, and large lines with unlimited buffer capacity, show the impacts of inter-arrival and processing time distributions on the inter-departure time variability. The inter-arrival time variability reduces the variability propagated by skewed processing time distributions, while larger skewness and kurtosis of the processing time distributions increase the inter-departure time variability.

Positively skewed processing time distributions amplify the variability of larger lines. However, this amplification effect due to increasing line size seems to have a lower impact on longer lines.

The mean inter-departure time never results affected by the processing time skewness and kurtosis and by the line size, which all impact only the variance of inter-departure times. The stage utilisation is crucial because when utilisation is close to 1, the line size and the inter-arrival and processing time distribution shapes have minor effects.

In the production field, all the potential causes of larger skewness (i.e., positive asymmetry) of the processing time distributions should be investigated and limited. In fact, the larger the skewness, the larger the amplification effect on the propagated variability.

Finally, the results shed light on those situations that can be immediately identified as more critical for the variability propagation by helping production and operation managers, practitioners, and process engineers to prioritise analyses, investigations, and further actions. For example, in the design and reconfiguration phases adding a new manufacturing stage in small systems creates relevant changes in the propagated variability, which is still more relevant when the processing time skewness is large. Instead, the additional variability propagated by adding a stage in a large size line has a marginal impact. However, the overall variability propagated by the distribution shape outperforms the line size effect.

This paper investigates the effects of the processing time distribution shapes by highlighting the connection between the moments of third and fourth order with the effect on the variability propagation. However, the distribution shape cannot be exactly described by the first four moments because also other factors can have an influence (such as the spread of the interquartile ranges and the moments of order higher than four). Therefore, the connection between distribution shape and skewness and kurtosis has to be considered as a measure of asymmetry rather than the effects on the variability propagation of specific values of skewness. Future research should assess if different distributions with different asymmetry can lead to different results although the same values of skewness and kurtosis.

Differently from what is suggested by the state-of-the-art literature, this work proves that the contribution of kurtosis might not be irrelevant. Hence, future research should try to separate the impacts of skewness and kurtosis.

Largely variable processing time distribution should be investigated to deepen the distribution shape behaviour in systems affected by high variability. Also, in future research, the effect on the variability of assembly/disassembly stages, the role of parallel machines, the position of bottlenecks in unbalanced lines, and other performance measures (e.g., WIP and CTq) should be investigated.

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