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Exploring the interplay of costs and flow time in Server Allocation for flow lines with parallel non-identical machines

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Abstract

The Server Allocation Problem is a significant challenge in manufacturing system design and consists of selecting both number and version of machines for each system stage. This optimisation problem is of outmost importance when there is a trade-off between minimizing investment costs and achieving target performance. This paper analyses the trade-off between minimising costs and flow time when allocating servers in hybrid flow lines with non-identical machines at each stage. The optimal design aims to minimise total costs and flow time while ensuring a target production rate. The paper proposes a bi-criteria approach that uses an efficient pattern-based problem representation and a Variable Neighborhood Search solution algorithm. An in-dept analysis of obtained solutions is performed. Additionally, a metric for comparing obtained solutions is proposed, providing insights for practical implementation. Comprehensive numerical analyses, considering scenarios with varying number of stages, machine versions, target performance, are performed to support the work.

Keywords: Server Allocation Problem, Production system design, Constrained Optimisation, Non-identical machines, Flow time.

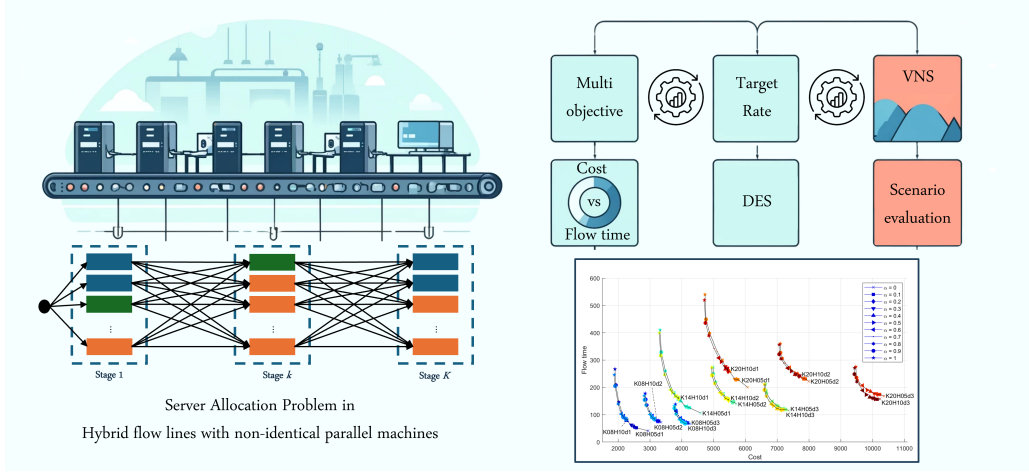


Figure 1: Graphical abstract

1. Introduction

One of the most critical decisions in the design of manufacturing systems is the allocation of resources among production stages and inter-stage buffers. In series-parallel production lines, also known as *hybrid flow lines*, parallel machines may be employed at each manufacturing stage, with work-in-process (WIP) held in buffers between two sequential stages. The design of such systems also requires the selection of resource versions from those available on the market. Machines in a stage can be either identical or non-identical, with the latter characterised by different speeds due to belonging to different versions [1, 2].

In this context, typical performance measures of interest include system total cost, production rate, as well as mean flow time, i.e. the average among all produced part of the time span between the beginning of the part's processing at the first manufacturing stage and its completion at the last manufacturing stage. Usually, the aim is to maximise the production rate, while total cost and the mean flow time might be minimised. Reducing the mean flow time can result in several benefits, such as lower work-in-process levels, improved quality, and reduced forecasting errors.

Flow time, as intended in this paper, includes the waiting time a part spends in buffers between stages and its total processing time. The literature shows that flow time is an important indicator of firm competitiveness since a flow time reduction positively affects the performance of production systems

[3, 4, 5, 6, 7].

Reducing flow time implies a reduction in the costs for handling and storing WIP inventories [8]. This is crucial for managing WIP that is subject to spoilage and obsolescence. This benefit is more significant for processes where the waiting time between operations must be limited, e.g. semiconductor [9], automotive [10], powder metallurgy [11]. Also, reducing flow time implies the possibility of quickly detecting quality problems, with a consequent early response to process detected deviations [12]. As flow time is strictly related to delivery lead time, reducing it leads to a reduction of response time to customer orders and to a most efficient management of the downstream supply chain [13].

This paper analyses the trade-off between minimizing the total cost and the flow time when optimally designing a hybrid flow line. The problem consists in selecting the number and version of machines at each stage, i.e. the *stage configuration*, with the aim of minimizing the total cost and the flow time while achieving a minimum target production rate. Each machine version is identified by its processing speed, which also determines its cost.

The paper is structured as follows: Section 2 presents a review of the related literature, Section 3 defines the problem, Section 4 addresses the proposed approach, and Section 5 discusses the design of experiments. The results obtained are analysed in Section 6, and managerial implications are discussed in Section 7. Section 8 concludes the paper with a discussion of its limitations and a proposed agenda for future research.

2. Literature Review and contribution

Scientific literature addressing the problem of optimally configuring production systems is wide [14, 15]. System configuration usually consists of allocating machines to the stages of a production system (Server Allocation Problem - SAP), buffer capacity between stages (Buffer Allocation Problem - BAP), machines and buffers together (known as BCAP), and workload (i.e., fraction of the total processing time) to each station (Workload Allocation Problem - WAP). This paper focuses specifically on the SAP with the aim of finding the best compromise in terms of total investment and flow time while addressing a target production rate. Thus, Section 2.1 outlines literature contribution on the topic and Section 2.2 states paper contributions with respect to the state of the art.

2.1. SAP review

SAP literature is herewith classified by distinguishing the contributions through the following main criteria: stage configuration (i.e. identical machines, non-identical machines) and decision variables. Further information are given about the key performance of interest, the evaluative method for assessing such performance and the generative approach (i.e. the optimisation method). A summary is provided in Table 1, in which the last row represents the features of the proposed research.

Table 1: SAP classification summary. Papers are divided in three groups according to the problem decision variables.

	Stage config.	Decision variables	Addressed KPIs									Evaluative method	Generative method				
Reference	Identical machines Non-identical machines	Machine versions Machine number Buffer size	Throughput Cost Flow time Tardiness Server capacity Buffer capacity Cycle time Workload Profit								Simulation Analytical approximation Meta-model	Branch and bound Exhaustive search Powell's search method Heuristics Others					
[16]	✓	✓	✓								✓					✓	
[17]	✓	✓	✓	✓		✓	✓				✓					✓	
[18]	✓	✓	✓	✓	✓		✓				✓	✓				✓	
[19]	✓	✓	✓	✓	✓						✓	✓					
[20]	✓	✓	✓	✓	✓						✓	✓					
[21]	✓	✓	✓	✓	✓						✓	✓					
[22]	✓	✓	✓	✓	✓						✓	✓					
[23]	✓	✓	✓	✓	✓						✓	✓					
[24]	✓	✓	✓	✓	✓					✓		✓				✓	
[25]	✓	✓	✓	✓	✓						✓	✓		✓			
[26]	✓	✓	✓	✓	✓					✓		✓					
[27]	✓	✓	✓	✓	✓						✓	✓					
[28]	✓	✓	✓	✓	✓							✓				✓	
[29]	✓	✓	✓	✓	✓					✓		✓					
[30]	✓	✓	✓	✓	✓						✓	✓					
[31]	✓	✓	✓	✓	✓						✓	✓					
[32]	✓	✓	✓	✓	✓						✓	✓					
[33]	✓	✓	✓	✓	✓						✓	✓					
[34]	✓	✓	✓	✓	✓						✓	✓					
[35]	✓	✓	✓	✓	✓						✓	✓					
[36]	✓	✓	✓	✓	✓						✓	✓					
[37]	✓	✓	✓	✓	✓						✓	✓					
[38]	✓	✓	✓	✓	✓						✓	✓				✓	
[39]	✓	✓	✓	✓	✓						✓	✓				✓	
This paper	✓	✓	✓	✓	✓	✓					✓					✓	

Identical machines with no machine version selection. The studies included in this paragraph select the number of parallel machines per stage without considering alternative versions. [18] assume an unlimited buffer capacity along the line, whilst [16, 19, 20, 22] assume a fixed and finite buffer capacity along the line, where [16] specifically considers zero-buffer systems. [17, 21, 23] address the BCAP. Cost and throughput are the main performance of interest as included in almost all the reviewed works. A bi-objective optimisation model is tackled by [16] (number of machines and throughput), while [17] considers a multi-objective problem (total number of machines, flow time and tardiness). As evaluative method, general open queuing networks are used in [16, 20, 21, 22, 23]. Whereas, Discrete Event Simulation (DES) is used in [17, 18, 19] to firstly build a meta-model that fits the performance metrics of the system. Simulation-optimisation is used to optimise the problems addressed by a meta-heuristic approach in [16, 17] and by a commercial software in [18]. The Powell’s search method is exploited by [21, 22, 23].

Identical machines with machine version selection. In addition to the number of parallel machines per stage, the studies included in this paragraph also consider the machine version, i.e. in terms of speed, as a decision variable, used in a certain stage. Some studies consider unlimited buffer capacities [25], while others optimise also the buffer capacity (BCAP) [24, 27, 29, 30, 31, 32, 34, 35, 36, 37, 38]. Analytical approximations and queuing networks are used in [30, 31, 32, 34, 24, 36, 37] to evaluate the performance of the production systems. DES is used in [25, 27, 29, 35, 38]. Specifically, a meta-model is built from the simulation estimates in [27, 29]. The papers mentioned in this group use various meta-heuristics as generative methods. Exceptions are [25] using a branch and bound approach, [27] proposing various multi-objective optimisation solution algorithms (weighted sum of objective functions, lexicographic ordering and goal programming), and [37] developing a decomposition coordination scheme. [26, 28, 32] analyse single server production line where only machine version (speed) is optimised jointly with buffer capacity. The approaches use approximate analytical evaluation procedures and heuristic-based generative methods.

Non-identical machines. The SAP with non-identical machines both within and through the stages has been recently addressed in [39]. Machine versions and numbers are selected throughout the production line and a simulation-optimisation solving approach is proposed to minimise the total cost.

1 2.2. Contribution of the paper

2 This paper presents a novel approach to address the Server Allocation
3 Problem (SAP) in hybrid flow lines with non-identical machines. The aim
4 is to analyse the trade-off between minimising the total cost and the flow
5 time, while satisfying a target production rate. A bi-criteria simulation-
6 optimisation approach is used to solve the problem. Furthermore, the *Man-*
7 *hattan distance* is proposed as metric to analyse the obtained solutions.

8 To the best of our knowledge, this is the first attempt to address the SAP
9 in hybrid flow lines with non-identical machines using a bi-criteria approach.
10 Our proposed method builds on a recently proposed approach for SAP with
11 non-identical machines that minimises the total cost under a target produc-
12 tion rate [39]. Differently from (author?) [39], in the present work (i) the
13 simulation procedure is able to estimate WIP and flow time in addition to
14 the processing rate; (ii) the solution algorithm addresses the bi-criteria rep-
15 resentation of the problem; (iii) a distance metric is proposed to compare
16 solutions by assessing how they differ in terms of stage configuration instead
17 of performance measures. A comprehensive analysis is arranged for demon-
18 strating the obtained results as enabled by the proposed bi-criteria approach.
19 The results will show that the bi-criteria approach leads to finding Pareto
20 efficient frontiers of solutions that minimise both the total costs and mean
21 flow time. An in-depth analysis of the found solutions is described, in which
22 solutions are compared by using the proposed distance metric.

23 3. Problem statement

24 The system under analysis is a hybrid flow line with K stages and $K - 1$
25 inter-stage buffers. Each stage k ($k = 1, 2, \dots, K$) may hold up to M_k parallel
26 machines that can be chosen from a set of versions available in the market.
27 Namely, H_k machine versions are available at each stage k . The following
28 assumptions are stated:

- 29 • Machines at the last stage are never blocked.
- 30 • Machine version H_k is characterised by a specific processing speed $s_{h,k}$
31 and cost $c_{h,k}$ so as the higher the cost, the larger the processing speed.
- 32 • Parts are assumed to belong to the same family, no due dates are
33 included, and parts flow through the stages of the line with a linear
34 flow.

- Parts are produced following a First Come - First Serve (FCFS) rule. 1
- The first stage never starves of raw parts. 2

The decision problem consists in finding the optimal resource configuration of the production system that respects a minimum production rate $\tilde{\theta}$. Thereby, a number of machines $m_{h,k}$ of version $h = 1, 2, \dots, H_k$, can be assigned to each stage $k = 1, 2, \dots, K$. In details, each stage k can be configured with $\sum_h m_{h,k}$ machine, even non-identical. 3 4 5 6 7

Let $\mathbf{x}$ denote the general system layout, whose production rate $\theta(\mathbf{x})$ is greater than the target $\tilde{\theta}$. The optimisation problem is: 8 9

$$\min F(\mathbf{x}) \quad (1) \quad 10$$

$$\text{s.t.} \quad \theta(\mathbf{x}) \geq \tilde{\theta} \quad (2) \quad 11$$

$$\sum_{h=1}^{H_k} m_{h,k} \leq M_k \quad \forall k \quad (3) \quad 12$$

$$m_{h,k} \in \mathbb{N}_0^+ \quad \forall k, h = 1, 2, \dots, H_k \quad (4) \quad 13$$

The objective is the minimization of the function $F(\mathbf{x})$ including two criteria: 14

- the resource cost C_t , defined as:

$$C_t(\mathbf{x}) = \sum_{k=1}^K \sum_{h=1}^{H_k} (m_{h,k} \cdot c_{h,k});$$

- the mean flow time $\Phi(\mathbf{x})$, computed as the mean of the time span between the exit time and the beginning of production of each part. 15 16

Bi-criteria optimisation is used, thus, given weight $\alpha \in [0, 1]$, the problem at hand (equations (1)–(4)) is defined as:

$$F(\mathbf{x}) = \alpha \cdot \frac{C_t(\mathbf{x})}{C_{t,norm}} + (1 - \alpha) \cdot \frac{\Phi(\mathbf{x})}{\Phi_{norm}} \quad (5)$$

where C_t and $\Phi(\mathbf{x})$ are scaled by factors $C_{t,norm}$ and Φ_{norm} for normalization purposes. The scaling approach is discussed in Section 4, together with the definition of the computation of the performance measures of the system. Constraint (2) provides that the system must reach a target throughput $\tilde{\theta}$. Constraints (3) assure that, for each stage k , the total number of machines does not exceed the limit M_k . 17 18 19 20 21 22

1 4. Description of the solution approach

2 In this Section, we briefly describe the solution approach used in the
 3 paper. The approach consists in: a pattern-based evaluative method to
 4 evaluate the performance measures of candidate solutions, and a Variable
 5 Neighborhood Search (VNS) meta-heuristic to generate new solutions.

6 4.1. The pattern-based encoding

7 A *pattern-based encoding* is used, which allows to condense information
 8 into a one-dimensional array with K integer components each representing
 9 the layout configuration selected in stage $k = 1 \dots K$.

10 The layout configuration of stage k is characterised by the number $m_{h,k}$ of
 11 installed machines of each version $h = 1 \dots H$. The total number of machines
 12 allocated to stage k is $\sum_h m_{h,k}$. A *pattern* is defined as a stage configuration,
 13 i.e. a one-dimensional array containing the number of installed machine
 14 versions: $p_k = [m_{1,k} \dots m_{H,k}]'$. The number of possible patterns, i.e. the
 15 number of possible combinations of machine versions, is defined as NP . The
 16 matrix of patterns $\mathbf{P}$ is composed of the complete enumeration of the NP
 17 possible patterns, listed in columns. A candidate solution $\mathbf{x}$ is a vector of K
 18 components, each including an integer value indicating the pattern index.

A numerical example is provided to illustrate the structure of the pattern-
 based encoding. Let us consider $H = 2$ machine variants and maximum
 $M_k = 2$ machines in a stage, the matrix $\mathbf{P}$ has $H = 2$ rows and $NP = 4$
 columns as follows:

$$\mathbf{P} = \begin{bmatrix} 0 & 1 & 1 & 2 & 0 \\ 1 & 0 & 1 & 0 & 2 \end{bmatrix} \quad (6)$$

19 The first column $[0 \ 1]'$ refers to a stage configuration that includes zero
 20 machines of the first variant and one of the second variant. A possible so-
 21 lution of a problem with $K = 3$ stages is $\mathbf{x} = \{1, 3, 2\}$, meaning that the
 22 first stage is configured with pattern $[0 \ 1]'$, the second with $[1 \ 1]'$, the third
 23 with $[1 \ 0]'$. There is no guarantee that a solution $\mathbf{x}$ composed of arbitrary
 24 patterns for each stage is feasible for the problem on-hand because of the
 25 target production rate. The evaluative method discussed in the following
 26 computes its performance measures, with which determining the feasibility
 27 of such solution.

4.2. The evaluative method

An evaluative procedure is used to simulate the behaviour of the line while processing parts and evaluate the performance measures of a candidate solution $\mathbf{x}$. In details, define $a_j(\mathbf{x})$ the arrival time of part j at the first stage (i.e., material availability time), $y_{j,k}(\mathbf{x})$ the loading time of part j on a machine of stage k , and $z_{j,k}(\mathbf{x})$ the completion time of part j from stage k . The mean production rate is computed by the exact estimate $\theta(\mathbf{x})$ obtained by simulating the production of N parts, i.e.:

$$\theta(\mathbf{x}) = \frac{N}{z_{N,K}(\mathbf{x})}. \quad (7)$$

The mean flow time $\Phi(\mathbf{x})$ is computed as:

$$\Phi(\mathbf{x}) = \frac{1}{N} \sum_{j=1}^N (z_{j,K}(\mathbf{x}) - a_j(\mathbf{x})). \quad (8)$$

For ease of completeness, the mean WIP level $W_k(\mathbf{x})$ for each buffer $k = 1, \dots, K - 1$ can be obtained by applying Little's Law [8]:

$$W_k(\mathbf{x}) = \frac{\sum_{j=1}^N (y_{j,k+1}(\mathbf{x}) - z_{j,k}(\mathbf{x}))}{N} \cdot \theta(\mathbf{x}) \quad \forall k = 1, \dots, K - 1. \quad (9)$$

The number of parts flowing in the system N has to be properly selected to find the better balance between accuracy of solutions and computational burden, as will be discussed in Section 5.

4.3. The objective function

The objective function is composed of the weighted sum of the normalised total cost and flow time, as given in equation (5). Specifically, the total cost $C_t(\mathbf{x})$ and the flow time $\Phi(\mathbf{x})$ are weighted by $\alpha \in [0, 1]$ and scaled by factors $C_{t,norm}$ and Φ_{norm} . The performance obtained by the initial solution $\mathbf{x}_0$ are used as: $C_{t,norm} = C_t(\mathbf{x}_0)$ and $\Phi_{norm} = \Phi(\mathbf{x}_0)$.

A static penalty is added to handle the production rate constraint [40, 41]. Therefore, the objective function of the problem combines two distinct terms is deployed, and the former consists of the bi-criteria function $F(\mathbf{x})$ as in equation (5). The latter is the penalty contribution that penalizes solutions

1 whose production rate is lower than the target value $\tilde{\theta}$. Hence, the resulting
2 objective function is as follows.

$$3 \quad f(C(\mathbf{x}), \Phi(\mathbf{x}), \theta(\mathbf{x})) = \left[\alpha \cdot \frac{C_t(\mathbf{x})}{C_{t,norm}} + (1 - \alpha) \cdot \frac{\Phi(\mathbf{x})}{\Phi_{norm}} \right] \cdot (1 + viol(\mathbf{x}))^\eta \quad (10)$$

4 where η is a coefficient regulating the intensity of penalty, which is set to
5 1,000 after a series of preliminary trials, and $viol$ is the term depending on
6 the magnitude of the constraint violation:

$$7 \quad viol(\mathbf{x}) = \max \left\{ \frac{\tilde{\theta} - \theta(\mathbf{x})}{\tilde{\theta}}, 0 \right\}. \quad (11)$$

8 4.4. The adopted generative method

9 The adopted generative method is a Variable Neighborhood Search (VNS),
10 which is a well known efficient meta-heuristic algorithm to solve combinato-
11 rial and non-linear optimisation problems [42, 43]. The VNS algorithm uses
12 a hierarchical approach to explore different neighborhood structures in a sys-
13 tematic way, with the aim of finding a new local optimum or near-optimal
14 solution during the evolutionary process. In particular, we adapted a recently
15 proposed VNS [39] to handle the new objective function that includes the
16 minimization of both total costs and mean flow time. The initial solution
17 required by the VNS algorithm is found by a constructive heuristic, *SAP-H*,
18 which guarantees a feasible solution. *SAP-H* is based on selecting at each
19 stage the pattern that guarantees an isolated production rate greater than
20 the target value in the less costly manner.

21 5. Description of scenario problems and instances

22 A benchmark of scenario problems was created for the experimental study.
23 A full factorial Design Of Experiments (DOE) is created by varying the
24 levels of three factors and comprises 18 scenario problems. Ten problem
25 instances are generated for each scenario by randomly sampling the remaining
26 parameters and the optimisation of each instance is replicated 10 times to
27 consider the randomness embedded in the VNS.

28 As for the bi-criteria approach proposed, experiments are repeated by
29 varying the value of the weight α from 0 to 1, with a discretisation step
30 of 0.1. The values $\alpha = 0$ and $\alpha = 1$ represent single-objective versions of

the problem, respectively the minimisation of the total cost and the flow time. Therefore, the numerical analysis includes a total of 19800 runs. All algorithms have been implemented in MATLAB[®] R2020b.

The 18 scenarios were generated by varying three factors: (i) the number of stages $K = \{8, 14, 20\}$, (ii) the number of available machine versions $H = \{5, 10\}$, and (iii) the production rate increment $\delta = \{1, 2, 3\}$. These factors impact on problem dimension and complexity. For ease of communication, we use a coded label to identify scenarios, as an example the label "K08H05d1" identifies the scenario with $K = 8$, $H = 5$ and $\delta = 1$.

In order to simplify the problem formulation without any lack in generality, we assume that there are $H_k = H$ machine versions available for each stage. The δ increment determines the target production rate $\tilde{\theta}$ of the problem. Indeed, δ is a non-negative increment of the minimum achievable production rate $\theta(\mathbf{x}_0)$ for a production system layout $\mathbf{x}_0$ where a single machine with the lowest speed and cost is used at each stage. In particular: $\tilde{\theta} = \theta(\mathbf{x}_0) \cdot (1 + \delta)$. This approach enables the computation of the maximum number of machines per stage M_k , such that the target production rate can be achieved solely by employing the less expensive machines.

Table 2 provides a summary of how processing times, machine costs and speeds were randomly sampled for instance generation. Jobs flow from stage $k = 1$ to stage $k = K$ without skipping, and their processing times are assumed to follow Lognormal distributions [44, 45]. Specifically, processing times at each stage are drawn from $\text{Log}(2, 1.5)$. Machine costs $c_{h,k}$ are sampled from a uniform distribution with a minimum of 100 and a maximum of 200 (i.e., $U(100, 200)$), and processing speeds $s_{h,k}$ are sampled from $U(1, 1.5)$. Part processing times are scaled according to the machine speed. The machines are sorted based on increasing costs for increasing processing speeds, with the slowest machine version set to have $s_{1,k} = 1$ for each stage k . In this context, the assumption of incremental cost relationship with machine speed (higher speed equals higher cost) is used without imposing a specific mathematical correlation between the two characteristics. Additionally, solutions featuring slow yet costly machines are dominated and are not meaningfully evaluated.

In the evaluative method, we have fixed the number of jobs N to 3,000, as this ensures that the simulation attains a stable steady-state for the production rate. We conducted a series of initial test runs using a random subset of the DOE and an increasing number of jobs for each scenario. The results showed that setting N to 3,000 resulted in an average percentage deviation

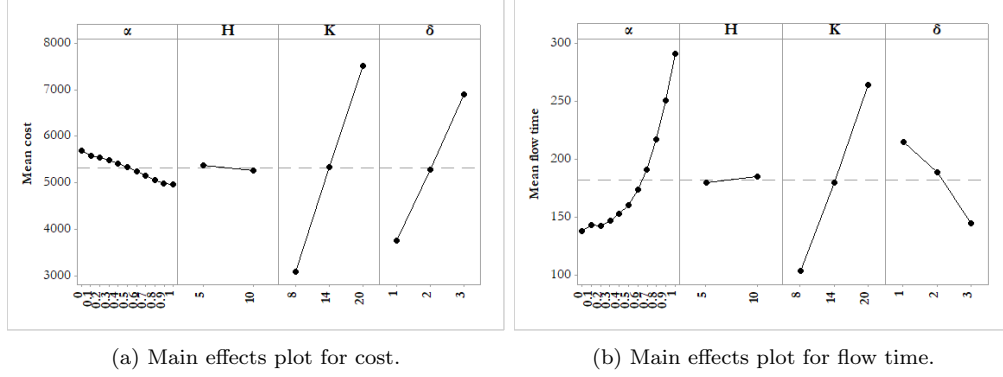


Figure 2: Mean values of flow time and cost, grouped by the factors of the DoE: α , K , H , δ .

- 1 of the throughput that was consistently lower than 5% compared to the same
- 2 metric evaluated in the same scenarios with N set to 100,000.

Parameters		
Description	Notation	Value
Number of jobs	N	3,000
Processing times distribution	t_{ik}	$\text{Log}(2, 1.5)$
Machine cost distribution	$c_{h,k}$	$\text{U}(100, 200)$
Machine speed distribution	$s_{h,k}$	$\text{U}(1, 1.5)$

Table 2: Design of experiment.

3 6. Numerical results and findings

4 6.1. Analysis of the performance

5 This section discusses the analysis of the evaluated performance measures
6 (flow time and cost), and their interaction with the experimental factors.

7 Figures 2 shows the mean effect plots related to the cost and the flow time,
8 respectively, grouped by the levels of each factor. According to Figure 2a, the
9 mean cost tends to decrease with increasing values of α , as its weight in the
10 objective function increases. Conversely, the mean flow time increases when α
11 increases (Figure 2b). By comparing the scales of Figures 2a and 2b, moving
12 from $\alpha = 0$ to $\alpha = 1$ implies a roughly 15% cost decrease, while it implies
13 a roughly 52.7% flow time increase. The impact of having more available

versions (H) is not statistically significant for the two performance measures of interest. Trivially, the mean cost and flow time increase for long lines (increasing K), as more stages are present in the system. Nevertheless, the mean cost per stage (i.e. C/K) tends to slowly decrease when K increases, being C/K on average equal to 384.8 for $K = 8$, 380.8 for $K = 14$, and 375.8 for $K = 20$, while the mean flow time per stage (i.e. Φ/K) does not show any particular tendency (being equal to 12.9 for $K = 8$, 12.8 for $K = 14$, and 13.2 for $K = 20$). The impact of δ is significantly increasing the mean cost and decreasing the mean flow time, as the throughput target is met with increasingly faster machines. However, moving from $\delta = 1$ to $\delta = 3$ implies a greater effect on the cost increase, which is equal to 84.7%, than the effect on the flow time decrease, which is 32.8%.

The interactions between flow time and cost are shown in Figure 3. For each scenario, the figure shows a bi-objective Pareto front between the cost (horizontal axis) and the flow time (vertical axis) for all α values. Each curve is identified by a scenario label located on the lower right corner. The blue, yellow and red color groups show the results for short ($K = 8$), medium ($K = 14$) and long ($K = 20$) lines respectively. Within the same group color, the three couples of curves are related to the three throughput increment ($\delta = 1$, $\delta = 2$ and $\delta = 3$ from left to right) and show that the larger the throughput target, the higher the related costs. Whereas, the flow time tends to be less influenced by α as δ increases (the curves becomes vertically shorter by increasing δ). The Pareto fronts appear in couples: for each combination of K and δ , the curves associated with $H = 5$ and $H = 10$ are almost overlapped with each other; this reveals a weak influence of H on both performance measures. This finding is aligned with the lack of significance of H as for Figure 2. However, the weak influence of H could be partially motivated by the higher computational effort required to achieve the local optima. In fact, moving from $H = 5$ to $H = 10$ available variants drastically increases the size of the possible patterns among which choosing the best stage configuration. For instance, in the case of a 8-stage line with $\delta = 1$, $H = 5$ implies having a 55×5 $\mathbf{P}$ matrix, while with $H = 10$ $\mathbf{P}$ is a 285×10 matrix. Thus, the solution space drastically increases with H and it is more difficult for the VNS to escape from local optima.

6.2. Analysis of solutions

This section focuses on the analysis of system configurations found as solution of the investigated scenarios. The heat-maps in Figures 4 and 5

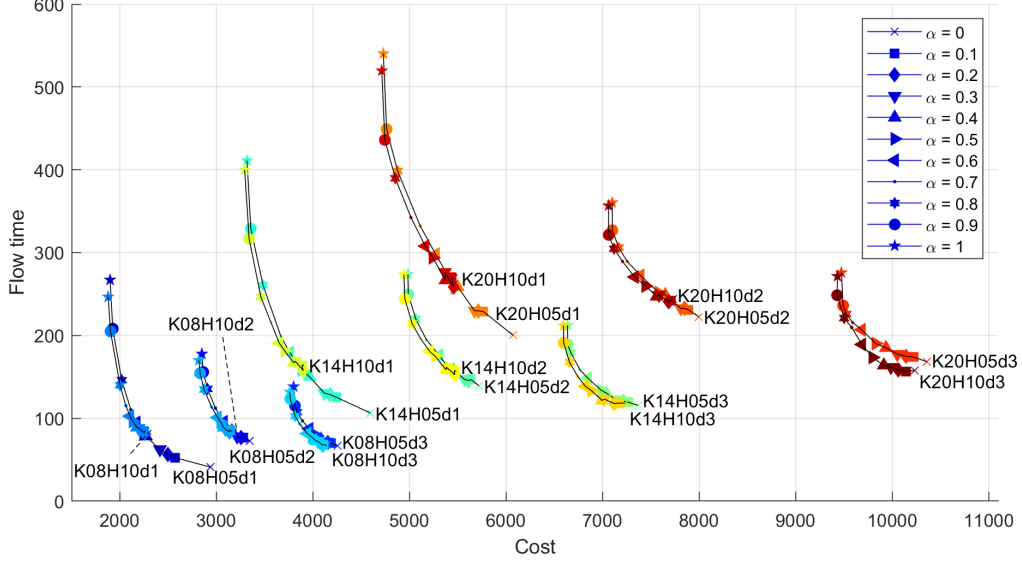


Figure 3: Flow time Vs cost: Pareto fronts at varying the experimental factors. Mean performance per scenario is reported.

1 allow inferring on the stage configurations to be adopted as both the problem
2 scenario (rows) and α (columns) change.

3 The mean number of machines per stage (Figure 4) increases with the
4 target increment of production rate δ . Such number is affected in a minimal
5 part by the weight α and the number of stages K , and it is not affected
6 by the number of available versions H . While the increase of the mean
7 number of machines per stage with increasing δ and decreasing K is intuitive,
8 attention should be given to the minimal change related to changing α values:
9 the change in the objective function does not affect the average production
10 capacity per stage. The stage configuration includes on average two parallel
11 machines to achieve a throughput twice the base one ($\delta = 1$), three when δ
12 is equal to 2, and almost four parallel machines when δ is equal to 3.

13 The mean number of variants per stage (Figure 5) increases with the
14 target increment of production rate δ and increases for decreasing α ; whereas,
15 it is not affected by the number of stages K and the available variants H .
16 The more importance is gained by the flow time (decreasing α), the more
17 variants are included in the same stage.

18 Table 3 reports the probability of finding a certain number of machine

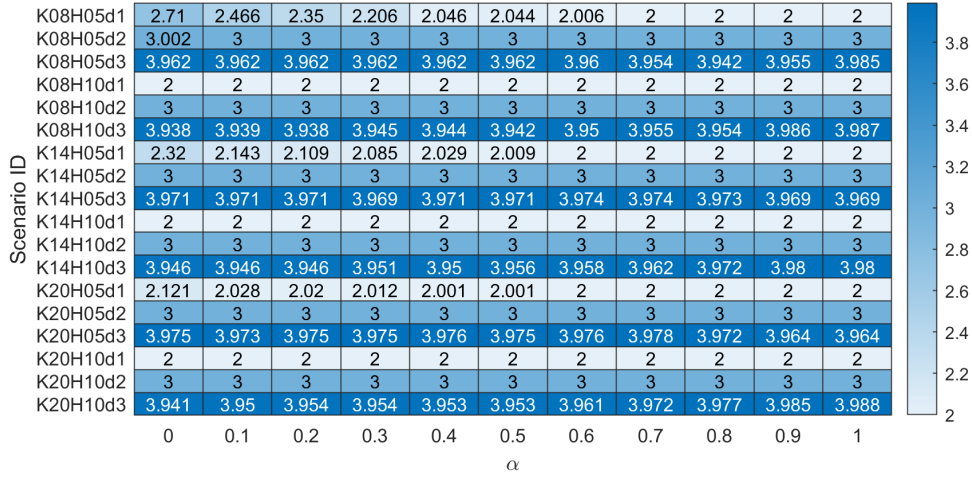


Figure 4: Mean number of machines per stage according to scenario and weight α .

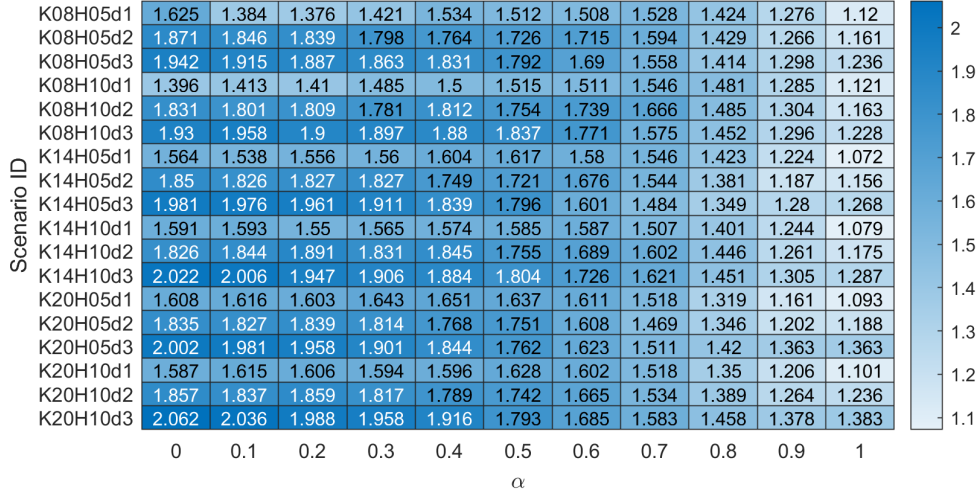


Figure 5: Mean number of variants per stage according to scenario and weight α .

1 variants in the same manufacturing stage. We can observe that a stage might
2 include up to 4 variants, and this finding implies that the best solutions
3 provide layouts with non-identical machines. Actually, most of the stages
4 includes one or two variants (from 93% probability with $\alpha = 0$, up to 99%
5 with $\alpha = 1$), and the probability of having a stage including machines with
6 a single variant increases with α . Such last finding reveals that for flow
7 time minimization purposes hybrid flow lines with non-identical machines
8 are preferable.

α	Number of variants			
	1	2	3	4
0	0.339	0.590	0.071	<0.001
0.1	0.330	0.608	0.062	-
0.2	0.330	0.610	0.060	<0.001
0.3	0.328	0.620	0.052	-
0.4	0.334	0.622	0.043	<0.001
0.5	0.361	0.603	0.036	-
0.6	0.425	0.547	0.027	<0.001
0.7	0.522	0.457	0.021	-
0.8	0.650	0.336	0.014	-
0.9	0.782	0.211	0.007	-
1	0.858	0.135	0.007	-

Table 3: Probability of having a stage configuration with non-identical machines according to weight α . No stage has been found equipped with more than 4 variants.

9 6.3. Comparative evaluation of solutions

10 This section aims at comparing the found solutions in terms of system
11 configuration to investigate the solution robustness and variability.

As the solutions of the analysed problem include complex stage configurations, a metric to effectively understand how different are the found configurations is needed. We use the *Manhattan distance* [46], a distance metric also known as *Taxicab geometry*, between two points in a n dimensional vector space, to compare the obtained solutions. Given two vectors $\mathbf{p} = \{p_1, p_2, \dots, p_n\}$ and $\mathbf{q} = \{q_1, q_2, \dots, q_n\}$, the *Manhattan distance* $\mathcal{L}^1(x_1, x_2)$ is defined as:

$$\mathcal{L}^1(\mathbf{p}, \mathbf{q}) = \sum_{i=1}^n |p_i - q_i|. \quad (12)$$

We compute $\mathcal{L}^1$ norm by comparing stage configurations in terms of number $m_{h,k}$ of machines of variant h in stage k . As illustrative example, let us consider $K = 2$, $H = 5$ and the following solutions $\mathbf{x}_1 = \{1\ 1\}$, $\mathbf{x}_2 = \{3\ 2\}$ and $\mathbf{x}_3 = \{3\ 8\}$ refer to the following patterns:

$$\begin{aligned}\mathbf{x}_1 &\rightarrow \mathbf{P}_{*,\mathbf{x}_1(1)} = [1\ 0\ 0\ 0\ 0]'; \mathbf{P}_{*,\mathbf{x}_1(2)} = [1\ 0\ 0\ 0\ 0]' \\ \mathbf{x}_2 &\rightarrow \mathbf{P}_{*,\mathbf{x}_2(1)} = [0\ 0\ 1\ 0\ 0]'; \mathbf{P}_{*,\mathbf{x}_2(2)} = [0\ 1\ 0\ 0\ 0]' \\ \mathbf{x}_3 &\rightarrow \mathbf{P}_{*,\mathbf{x}_3(1)} = [0\ 0\ 1\ 0\ 0]'; \mathbf{P}_{*,\mathbf{x}_3(2)} = [0\ 2\ 0\ 0\ 0]'\end{aligned}$$

Therefore:

$$\begin{aligned}\mathcal{L}^1(\mathbf{x}_1, \mathbf{x}_2) &= \sum_{k=1}^K \sum_{h=1}^H |\mathbf{P}_{h,\mathbf{x}_1(k)} - \mathbf{P}_{h,\mathbf{x}_2(k)}| = 4 \\ \mathcal{L}^1(\mathbf{x}_1, \mathbf{x}_3) &= \sum_{k=1}^K \sum_{h=1}^H |\mathbf{P}_{h,\mathbf{x}_1(k)} - \mathbf{P}_{h,\mathbf{x}_3(k)}| = 5 \\ \mathcal{L}^1(\mathbf{x}_2, \mathbf{x}_3) &= \sum_{k=1}^K \sum_{h=1}^H |\mathbf{P}_{h,\mathbf{x}_2(k)} - \mathbf{P}_{h,\mathbf{x}_3(k)}| = 1\end{aligned}$$

The used metric enables to compare solutions in terms of actual stage configuration. For small $\mathcal{L}^1$, two solutions are quite similar in terms of layout; whilst large $\mathcal{L}^1$ indicates a significant difference. Referring to the provided example, the system configurations $\mathbf{x}_1, \mathbf{x}_2$ have the same amount of machines in total but their variants change; configurations $\mathbf{x}_1, \mathbf{x}_3$ are different both in number and variants of machines, and configuration $\mathbf{x}_3$ only include an additional machine of the same stage in the second stage with respect to $\mathbf{x}_2$.

Given a scenario instance, we compute the $\mathcal{L}^1$ norm between the best solution found and the solutions found in the other 9 replicates of the same problem instance; then we compute the mean per scenario of the obtained results and we show the mean $\mathcal{L}^1$ norm in Figure 6.

It can be noticed that the value of the mean $\mathcal{L}^1$ increases from top to bottom of Figure 6. Indeed:

- as the line length increases (K), more stages are compared in each computation;
- as δ increases, the set of feasible solutions that tightly respect the throughput constraint increases, and the system configurations meeting the constraint increases;

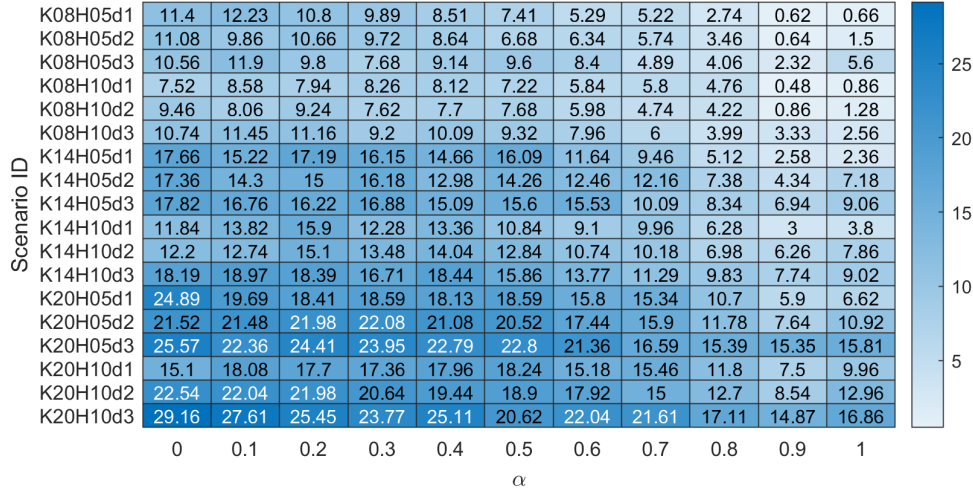


Figure 6: Mean Manhattan distance according to scenario and weight α .

- the number of variants H is not significantly affecting the results.

By analysing Figure 6 from right to left, the impact of the objective function and the related modification in the space of solutions is highly significant. The mean $\mathcal{L}^1$ norm almost triples as α decreases showing that the solutions found in replicates of the same instance are more different from each other as the flow time portion of the objective function increases its importance. Instead, for large values of α , the solutions found in replicates of the same instance appear to be very similar to each other (small $\mathcal{L}^1$), rather than equals ($\mathcal{L}^1 = 0$). This is especially true for scenarios in which δ is low.

Flow time minimization incurs in a smoother objective compared to cost minimization since the decision variables of the SAP are discrete. Indeed, the integer nature of the SAP is grounded onto the number of parallel machines and the number of available variants, both integer variables which directly affect the cost of a certain system configuration $\mathbf{x}$. Whereas, by modifying a stage configuration, the effect on the flow time might not be evident.

7. Managerial implications

In light of the numerical results presented and commented in the previous section, a series of managerial implications can be drawn to further support the decision-making issue of production system designers. Usually, both

flow time and costs are relevant in designing production systems. Thus, bi-objective optimisation could be preferable or necessary to optimize them together.

A first worthy insight regards the impact of α and δ on both the cost and the flow time variation. In brief, an increase from α equal to 0 to α equal to 1 would imply a mean cost saving equal about to 15% and simultaneously a mean flow time increase equal about to 53%. Hence, it is worthy to point out that a cost-oriented design optimisation would lead to a strong detrimental effect on the flow time performance. Indeed, when more weight is given to the flow time (i.e., when α tends to 0 in Figure 2), the flow time percentage improvement is larger than the cost percentage deterioration. This may be relevant in industries in which the delivery lead time offered to customer is critical, such as automotive or aircraft spare parts. Under that perspective, it is advisable for a decision maker to consider a smoother weight combination between cost and flow time when searching for the best layout configuration. On the other hand, whenever the target throughput grows from level 1 to level 3, the average cost increase is equal about to 85%, while the flow time decrease is roughly 33%. Again, it is a useful insight that makes the decision makers aware about the cost impact arising from setting the δ target to a high value, and the relatively low flow time reduction as well.

Looking at the results related to the average number of machines per stage (Figure 4), it is clear that the higher the throughput target, the higher such metric value, which in turns is slightly sensitive to the number of stages (K) and the objective function weight (α). In other words, whether a decision maker looks for a significantly higher throughput, the number of machines per stage must be increased by one unit. Hence, two machines per stage are enough on the average to assure a 100% throughput increment. Instead, three and four machines per stage must be taken on if the throughput target is two or three times higher than the current one. Interestingly, such managerial implications hold whatever the values of α , K and H .

Beyond the managerial insights on the average number of machines per stage, another guideline emerging from the numerical results concerns the average number of variants per stage (Figure 5). It appears that on average just one machine variant per stage or little more are sufficient to minimize the cost of equipment, while the flow time minimization is more sensitive to the machine variants; thus, an average number of machine variants close to two is required at each stage when the objective is flow time-oriented. In general, the average number of machine variants per stage should be set to

two when the throughput target is three times the reference value. On the other hand, such metric could be reduced roughly to 1.8 and 1.6 when the target δ is equal to two and three, respectively.

Finally, the Manhattan distance metrics allows to infer on the best layout configuration. Figure 6 gives information on the solution diversity at varying the several parameters. What emerges is that a low solution diversity exists when the objective is cost-oriented and the number of machines is low. In other words, the uncertainty on the selected layout configuration is quite weak. Conversely, a higher diversity of solution in terms of layout comes out when the objective holds a higher flow time component and the line is longer. In this latter scenario, the choices of the decision maker on the best layout configuration could be more uncertain and the expected performance as well.

8. Conclusive remarks and future developments

The bi-criteria SAP for hybrid flow lines is addressed in this paper to minimise the investment cost and the flow time while meeting a target throughput. A Variable Neighbourhood Search algorithm is used to solve the bi-criteria problem, and an in-dept analysis of the solutions is performed.

The objective of the paper was to analyse the impact of various system characteristics on the solutions in terms of both flow time and investment cost. To this aim, a comprehensive design of experiments involving three influencing factors at different levels has been arranged. The factors are: the number of stages, the number of available machine versions and the throughput increment. The numerical results showed the impact of such factors on both flow time and investment cost. Also, the Manhattan distance metric has been used to assess the differences in the found system configurations when varying the factor levels. Managerial implication has been drawn to help decision makers in designing production system.

Future effort could be devoted to investigate the bi-criteria SAP under different assumptions such as different machine versions or multi-product environments, or by including other significant criteria such as the operative cost of the line, or the energy consumption. New advanced optimisation methods might be needed to address such new problems. A reconfiguration problem can be evaluated in the future where the cost of dismissing old machines present in the system is included.

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1 Data Availability Statement

2 The data that support the findings of this study are available from the
3 corresponding author, A.C, upon reasonable request.

4 References

- 5 [1] R. W. Conway, L. W. Miller, W. L. Maxwell, Theory of scheduling,
6 Dover, 2003.
- 7 [2] M. Pinedo, Scheduling, Vol. 29, Springer, 2012.
- 8 [3] W. J. Hopp, M. L. Spearman, Factory physics: Foundations of manu-
9 facturing management., Boston: Irwin/McGraw-Hill, 2001.
- 10 [4] D. J. Johnson, A framework for reducing manufacturing through-
11 put time, Journal of Manufacturing Systems 22 (4) (2003) 283–298.
12 doi:https://doi.org/10.1016/S0278-6125(03)80009-2.
- 13 [5] S. Wadhwa, K. Rao, F. Chan, Comparative influence of three flexibility
14 types on manufacturing lead-time performance, International Journal
15 of Advanced Manufacturing Technology 29 (9-10) (2006) 1002 – 1007.
16 doi:10.1007/s00170-005-2603-3.
- 17 [6] J. Li, D. E. Blumenfeld, N. Huang, J. M. Alden, Throughput anal-
18 ysis of production systems: recent advances and future topics, Inter-
19 national Journal of Production Research 47 (14) (2009) 3823–3851.
20 doi:10.1080/00207540701829752.
- 21 [7] S. Serdarasan, A review of supply chain complexity drivers,
22 Computers & Industrial Engineering 66 (3) (2013) 533–540.
23 doi:10.1016/j.cie.2012.12.008.
- 24 [8] J. D. C. Little, A proof for the queuing formula: $l = \lambda w$, Operations
25 Research 9(3) (1961) 383–387.
- 26 [9] D. Kopp, M. Hassoun, A. Kalir, L. Mönch, Integrating criti-
27 cal queue time constraints into smt2020 simulation models, in:
28 2020 Winter Simulation Conference (WSC), 2020, pp. 1813–1824.
29 doi:10.1109/WSC48552.2020.9383889.

- [10] R. E. deMatta, Minimizing the total waiting time of intermediate products in a manufacturing process, *Int. Trans. Oper. Res.* 26 (2019) 1096–1117. doi:10.1111/itor.12343. 1
2
3
- [11] Y. Wang, L. Li, Heterogeneous redundancy allocation for series-parallel multi-state systems using hybrid particle swarm optimization and local search, *IEEE Transactions on Systems, Man, and Cybernetics, Part A* 42 (2012) 464–474. 4
5
6
7
- [12] L. Cuatrecasas-Arbós, J. Fortuny-Santos, P. Ruiz-de Arbulo-López, C. Vintró-Sánchez, Monitoring processes through inventory and manufacturing lead time, *Industrial Management & Data Systems.* 8
9
10
- [13] S. De Treville, R. D. Shapiro, A.-P. Hameri, From supply chain to demand chain: the role of lead time reduction in improving demand chain performance, *Journal of operations management* 21 (6) (2004) 613–627. 11
12
13
- [14] D. Bergeron, M. A. Jamali, H. Yamamoto, Modelling and analysis of manufacturing systems: a review of existing models, *International Journal of Product Development* 10 (1-3) (2010) 46–61. 14
15
16
- [15] C. T. Papadopoulos, J. Li, M. E. O’Kelly, A classification and review of timed markov models of manufacturing systems, *Computers & Industrial Engineering* 128 (2019) 219–244. 17
18
19
- [16] R. Andriansyah, T. Van Woensel, F. R. Cruz, L. Duczmal, Performance optimization of open zero-buffer multi-server queueing networks, *Computers & Operations Research* 37 (8) (2010) 1472–1487. 20
21
22
- [17] A. Baykasoğlu, Gene expression programming based meta-modelling approach to production line design, *International Journal of Computer Integrated Manufacturing* 21 (6) (2008) 657–665. 23
24
25
- [18] B. Dengiz, T. Bektas, A. E. Ultanir, Simulation optimization based dss application: A diamond tool production line in industry, *Simulation Modelling Practice and Theory* 14 (3) (2006) 296 – 312. 26
27
28
- [19] B. Dengiz, Y. T. İç, O. Belgin, A meta-model based simulation optimization using hybrid simulation-analytical modeling to increase the productivity in automotive industry, *Mathematics and Computers in Simulation* 120 (2016) 120–128. 29
30
31
32

- 1 [20] K. Futamura, The multiple server effect: Optimal allocation of servers
2 to stations with different service-time distributions in tandem queueing
3 networks, *Annals of Operations Research* 93 (1-4) (2000) 71–90.
- 4 [21] H. d. S. R. Martins, F. R. Cruz, A. R. Duarte, F. L. Oliveira, Model-
5 ing and optimization of buffers and servers in finite queueing networks,
6 *OPSEARCH* 56 (1) (2019) 123–150.
- 7 [22] J. M. Smith, F. Cruz, T. van Woensel, Optimal server allocation in gen-
8 eral, finite, multi-server queueing networks, *Applied Stochastic Models*
9 *in Business and Industry* 26 (6) (2010) 705–736.
- 10 [23] T. Van Woensel, R. Andriansyah, F. R. Cruz, J. M. Smith, L. Kerbache,
11 Buffer and server allocation in general multi-server queueing networks,
12 *International Transactions in Operational Research* 17 (2) (2010) 257–
13 286.
- 14 [24] J. E. Abu Qudeiri, H. Yamamoto, R. Ramli, A. Jamali, Genetic algo-
15 rithm for buffer size and work station capacity in serial-parallel produc-
16 tion lines, *Artificial Life and Robotics* 12 (2008) 102–106.
- 17 [25] S. Almutawa, M. Savsar, K. Al-Rashdan, Optimum machine selection in
18 multistage manufacturing systems, *International Journal of Production*
19 *Research* 43 (6) (2005) 1109–1126.
- 20 [26] A. Artiba, F. Riane, M. Nourelfath, N. Nahas, D. Ait-Kadi, Optimal de-
21 sign of series production lines with unreliable machines and finite buffers,
22 *Journal of Quality in Maintenance Engineering*.
- 23 [27] O. Feyzioglu, H. Pierreval, D. Deflandre, A simulation-based optimiza-
24 tion approach to size manufacturing systems, *International Journal of*
25 *Production Research* 43 (2005) 247–266.
- 26 [28] K.-C. Jeong, Y.-D. Kim, Heuristics for selecting machines and deter-
27 mining buffer capacities in assembly systems, *Computers & industrial*
28 *engineering* 38 (3) (2000) 341–360.
- 29 [29] M. M. Motlagh, P. Azimi, M. Amiri, G. Madraki, An efficient simulation
30 optimization methodology to solve a multi-objective problem in unre-
31 liable unbalanced production lines, *Expert Systems with Applications*
32 138 (2019) 112836.

- [30] N. Nahas, N. Mustapha, D. Ait-Kadi, Ant colonies for structure optimization in a failure prone series-parallel production system, *Journal of Quality in Maintenance Engineering* 14 (2008) 7–33. 1 2 3
- [31] N. Nahas, M. Nourelfath, D. Ait-Kadi, Selecting machines and buffers in unreliable series-parallel production lines, *International Journal of Production Research* 47 (14) (2009) 3741–3774. 4 5 6
- [32] N. Nahas, M. Nourelfath, M. Gendreau, Selecting machines and buffers in unreliable assembly/disassembly manufacturing networks, *International Journal of Production Economics* 154 (2014) 113–126. 7 8 9
- [33] N. Nahas, M. Nourelfath, Joint optimization of maintenance, buffers and machines in manufacturing lines, *Engineering Optimization* 50 (1) (2018) 37–54. 10 11 12
- [34] N. Nahas, Buffer allocation, equipment selection and line balancing optimisation in unreliable production lines, *European Journal of Industrial Engineering* 14 (2) (2020) 217–246. 13 14 15
- [35] S. Spieckermann, K. Gutenschwager, H. Heinzl, H. Vob, Simulation-based optimization in the automotive industry - a case study on body shop design, *Transactions of The Society for Modeling and Simulation International - SIMULATION* 75. 16 17 18 19
- [36] D. Spinellis, C. Papadopoulos, J. M. Smith, Large production line optimization using simulated annealing, *International Journal of Production Research* 38 (3) (2000) 509–541. 20 21 22
- [37] S. Xi, J. M. Smith, Q. Chen, N. Mao, H. Zhang, A. Yu, Simultaneous machine selection and buffer allocation in large unbalanced series-parallel production lines, *International Journal of Production Research* 60 (7) (2022) 2103–2125. 23 24 25 26
- [38] M. F. Yegul, F. S. Erenay, S. Striepe, M. Yavuz, Improving configuration of complex production lines via simulation-based optimization, *Computers & Industrial Engineering* 109 (2017) 295–312. 27 28 29
- [39] A. Costa, E. Pastore, N. Frigerio, The server allocation problem with non-identical machines: A meta-heuristic approach, *Computers & Industrial Engineering* 162 (2021) 107687. doi:10.1016/j.cie.2021.107687. 30 31 32

- 1 [40] Ö. Yeniay, Penalty function methods for constrained optimization
2 with genetic algorithms, *Mathematical and computational Applications*
3 10 (1) (2005) 45–56.
- 4 [41] S. Alice, C. David, Penalty functions handbook of evolutionary compu-
5 tation, section c 5.2 (1996).
- 6 [42] N. Mladenović, P. Hansen, Variable neighborhood search, *Computers &*
7 *operations research* 24 (11) (1997) 1097–1100.
- 8 [43] P. Hansen, N. Mladenović, R. Todosijević, S. Hanafi, Variable neigh-
9 borhood search: basics and variants, *EURO Journal on Computational*
10 *Optimization* 5 (3) (2017) 423–454.
- 11 [44] A. Costa, A. Alfieri, A. Matta, S. Fichera, A parallel tabu search for
12 solving the primal buffer allocation problem in serial production systems,
13 *Computers & Operations Research* 64 (2015) 97–112.
- 14 [45] A. Alfieri, A. Matta, E. Pastore, A column generation algorithm for
15 the buffer allocation problem approximated by the time buffer concept,
16 *IFAC-PapersOnLine* 49 (12) (2016) 739–744.
- 17 [46] F. Riesz, Untersuchungen über systeme integrierbarer funktionen, *Math-*
18 *ematische Annalen* 69 (1910) 449–497. doi:10.1007/BF01457637.

Appendix A. Descriptive statistics of performance measures

This section includes three tables showing the average values and the standard errors (i.e., the standard deviation divided by the squared root of the number of observations) of throughput, flow time and cost. The values are shown for each scenario and each α value. Tables A.4-A.5-A.6 show the results for scenarios with 8, 14, and 20 stages respectively.

Scenario	α	TH		Flow Time		Cost	
		<i>avg</i>	<i>see</i>	<i>avg</i>	<i>see</i>	<i>avg</i>	<i>see</i>
K08H05d1	0	0.55	0.00	41.07	1.05	2938.59	21.13
	0.1	0.55	0.00	52.39	1.29	2573.30	14.01
	0.2	0.55	0.00	56.56	1.09	2498.47	13.46
	0.3	0.55	0.00	62.47	0.95	2414.19	12.42
	0.4	0.54	0.00	78.41	0.89	2268.72	11.18
	0.5	0.54	0.00	80.94	1.25	2244.13	10.22
	0.6	0.54	0.00	95.01	1.83	2171.20	11.18
	0.7	0.54	0.00	110.29	2.45	2113.19	10.41
	0.8	0.54	0.00	146.03	3.10	2019.20	8.77
	0.9	0.53	0.00	208.22	5.87	1926.07	6.96
	1	0.52	0.00	267.09	6.59	1898.32	7.49
K08H05d2	0	0.81	0.00	72.56	1.34	3343.61	16.82
	0.1	0.81	0.00	76.52	1.35	3278.89	15.24
	0.2	0.81	0.00	76.49	1.37	3252.28	14.48
	0.3	0.81	0.00	77.99	1.40	3213.13	12.27
	0.4	0.81	0.00	84.35	1.79	3159.95	11.79
	0.5	0.81	0.00	86.28	2.14	3130.07	12.79
	0.6	0.80	0.00	95.74	2.08	3074.44	13.73
	0.7	0.80	0.00	112.20	2.36	2989.92	13.74
	0.8	0.79	0.00	135.52	3.69	2907.85	12.07
	0.9	0.78	0.00	155.88	3.21	2862.97	10.75
	1	0.78	0.00	177.78	3.43	2848.70	11.22
K08H05d3	0	1.06	0.00	66.75	1.48	4252.73	18.51
	0.1	1.06	0.00	70.08	1.76	4186.67	16.39
	0.2	1.06	0.00	70.71	1.72	4151.97	14.84
	0.3	1.06	0.00	71.64	1.71	4132.62	13.77
	0.4	1.06	0.00	74.53	1.68	4083.11	14.10
	0.5	1.06	0.00	79.28	1.84	4033.30	15.15
	0.6	1.05	0.00	87.39	2.12	3962.28	13.54
	0.7	1.04	0.00	96.92	2.49	3891.05	12.64
	0.8	1.04	0.00	107.51	2.80	3835.16	14.45
	0.9	1.04	0.00	115.20	2.41	3813.13	15.54
	1	1.04	0.00	138.25	2.30	3799.67	14.55
K08H10d1	0	0.54	0.00	83.92	1.01	2263.28	8.05
	0.1	0.54	0.00	84.93	1.08	2251.34	8.38

	0.2	0.54	0.00	81.92	1.04	2254.68	8.56
	0.3	0.54	0.00	88.17	1.03	2193.51	9.15
	0.4	0.54	0.00	89.05	1.05	2176.51	8.46
	0.5	0.54	0.00	96.20	1.27	2134.54	7.96
	0.6	0.54	0.00	102.63	1.18	2104.63	7.98
	0.7	0.54	0.00	115.21	2.23	2061.82	7.29
	0.8	0.54	0.00	139.85	2.93	2001.29	6.51
	0.9	0.53	0.00	205.00	5.56	1902.32	6.22
	1	0.52	0.00	246.53	3.72	1878.24	5.92
K08H10d2	0	0.81	0.00	84.20	1.61	3162.87	13.05
	0.1	0.81	0.00	85.70	1.71	3138.61	11.71
	0.2	0.81	0.00	83.30	1.49	3138.28	10.56
	0.3	0.81	0.00	86.99	1.55	3092.23	10.76
	0.4	0.81	0.00	88.97	1.68	3075.97	10.87
	0.5	0.81	0.00	95.48	1.95	3044.16	10.44
	0.6	0.80	0.00	100.97	2.15	3011.71	10.95
	0.7	0.80	0.00	113.56	2.21	2949.28	7.82
	0.8	0.79	0.00	134.82	3.38	2872.02	10.50
	0.9	0.78	0.00	154.41	3.08	2830.41	8.89
	1	0.78	0.00	169.93	2.59	2816.83	8.75
K08H10d3	0	1.05	0.00	67.29	1.34	4143.97	16.32
	0.1	1.05	0.00	68.25	1.34	4107.88	13.23
	0.2	1.05	0.00	67.63	1.23	4101.24	11.80
	0.3	1.05	0.00	72.38	1.28	4049.13	12.71
	0.4	1.05	0.00	72.63	1.22	4032.21	11.46
	0.5	1.05	0.00	77.34	1.21	3987.61	10.05
	0.6	1.05	0.00	81.67	1.42	3940.19	10.22
	0.7	1.05	0.00	93.30	1.90	3862.19	11.96
	0.8	1.04	0.00	102.46	1.75	3814.01	12.38
	0.9	1.04	0.00	123.60	2.26	3764.77	11.74
	100	1.04	0.00	131.97	2.25	3758.89	11.53

Table A.4: Average and standard error values of throughput, flow time and cost of scenarios with $K = 8$.

Scenario	α	TH		Flow Time		Cost	
		<i>avg</i>	<i>see</i>	<i>avg</i>	<i>see</i>	<i>avg</i>	<i>see</i>
K14H05d1	0	0.54	0.00	106.36	1.59	4594.07	26.58
	0.1	0.54	0.00	125.32	1.45	4244.03	14.56
	0.2	0.54	0.00	128.67	1.56	4175.13	14.73
	0.3	0.54	0.00	130.55	1.31	4116.05	14.58
	0.4	0.54	0.00	150.18	1.61	3965.49	12.15
	0.5	0.53	0.00	158.13	1.88	3881.21	13.79
	0.6	0.53	0.00	179.39	2.21	3759.99	13.55

	0.7	0.53	0.00	199.19	2.55	3666.33	13.11
	0.8	0.52	0.00	260.72	4.42	3482.60	10.85
	0.9	0.51	0.00	329.03	5.55	3355.97	7.09
	1	0.50	0.00	411.09	8.49	3316.3	8.38
K14H05d2	0	0.79	0.00	139.26	2.05	5720.32	13.37
	0.1	0.79	0.00	146.90	2.06	5633.67	12.64
	0.2	0.79	0.00	145.41	2.00	5611.27	10.88
	0.3	0.79	0.00	147.20	1.84	5568.31	10.92
	0.4	0.79	0.00	158.70	1.99	5455.84	11.33
	0.5	0.79	0.00	160.15	2.09	5412.86	13.26
	0.6	0.78	0.00	176.04	2.30	5305.17	14.16
	0.7	0.78	0.00	194.92	2.70	5174.72	13.87
	0.8	0.77	0.00	219.81	3.27	5065.02	11.42
	0.9	0.76	0.00	249.64	2.84	4986.60	11.77
	1	0.75	0.00	273.82	3.98	4983.40	11.87
K14H05d3	0	1.03	0.00	115.57	2.57	7367.33	15.67
	0.1	1.03	0.00	119.44	2.64	7267.81	15.21
	0.2	1.03	0.00	120.75	2.62	7214.32	14.52
	0.3	1.03	0.00	122.61	2.55	7138.48	14.11
	0.4	1.02	0.00	130.40	2.51	7038.82	14.82
	0.5	1.02	0.00	133.79	2.50	6985.79	15.79
	0.6	1.02	0.00	148.52	2.88	6845.74	12.63
	0.7	1.01	0.00	158.62	2.96	6764.93	13.46
	0.8	1.01	0.00	179.53	2.65	6669.87	15.49
	0.9	1.01	0.00	189.25	2.59	6638.08	16.11
	1	1.01	0.00	212.18	2.82	6637.44	15.69
K14H10d1	0	0.53	0.00	164.17	1.65	3906.39	8.73
	0.1	0.53	0.00	163.96	1.64	3884.83	8.25
	0.2	0.54	0.00	157.65	1.60	3900.25	9.38
	0.3	0.53	0.00	168.90	1.64	3815.96	8.31
	0.4	0.53	0.00	167.17	1.55	3800.21	8.13
	0.5	0.53	0.00	181.40	1.90	3707.06	7.14
	0.6	0.53	0.00	190.76	2.09	3650.26	9.30
	0.7	0.53	0.00	215.97	2.69	3563.72	9.81
	0.8	0.52	0.00	246.70	3.55	3459.59	10.92
	0.9	0.51	0.00	316.56	5.74	3338.52	7.38
	1	0.50	0.00	399.84	6.84	3292.37	6.33
K14H10d2	0	0.79	0.00	156.92	2.05	5484.66	9.97
	0.1	0.79	0.00	157.45	2.17	5463.67	9.75
	0.2	0.79	0.00	152.65	1.97	5467.95	8.55
	0.3	0.79	0.00	161.67	2.12	5382.59	7.71
	0.4	0.79	0.00	158.57	1.99	5377.62	8.24
	0.5	0.78	0.00	175.20	2.27	5264.18	9.89
	0.6	0.78	0.00	180.77	2.56	5208.95	10.26
	0.7	0.78	0.00	196.36	2.63	5113.58	10.06

	0.8	0.77	0.00	214.39	3.33	5027.1	10.12
	0.9	0.76	0.00	244.25	2.81	4951.49	9.92
	1	0.75	0.00	273.45	4.14	4941.27	9.87
K14H10d3	0	1.02	0.00	118.32	2.72	7230.20	14.03
	0.1	1.02	0.00	118.41	2.74	7171.83	12.40
	0.2	1.02	0.00	117.86	2.61	7121.60	10.99
	0.3	1.02	0.00	123.21	2.71	7018.76	13.77
	0.4	1.02	0.00	121.67	2.61	6992.94	14.55
	0.5	1.02	0.00	133.37	2.72	6885.11	13.66
	0.6	1.02	0.00	138.60	2.86	6820.73	13.60
	0.7	1.01	0.00	149.99	3.12	6745.40	13.78
	0.8	1.01	0.00	167.73	2.51	6656.88	15.51
	0.9	1.01	0.00	191.14	2.57	6596.73	13.41
	1	1.01	0.00	211.71	2.78	6594.07	13.56

Table A.5: Average and standard error values of throughput, flow time and cost of scenarios with $K = 14$.

Scenario	α	TH		Flow Time		Cost	
		avg	see	avg	see	avg	see
K20H05d1	0	0.53	0.00	200.25	2.94	6072.39	35.87
	0.1	0.53	0.00	229.03	2.90	5762.51	17.85
	0.2	0.53	0.00	229.73	2.96	5710.86	15.47
	0.3	0.53	0.00	229.80	2.92	5674.13	13.94
	0.4	0.52	0.00	258.61	3.55	5499.69	13.38
	0.5	0.52	0.00	257.53	3.25	5468.64	12.94
	0.6	0.52	0.00	298.19	4.32	5270.42	9.23
	0.7	0.51	0.00	332.10	5.76	5110.96	13.99
	0.8	0.50	0.00	398.61	4.93	4876.69	12.74
	0.9	0.50	0.00	449.03	4.36	4762.68	8.93
	1	0.49	0.00	540.28	7.87	4728.92	8.93
K20H05d2	0	0.77	0.00	222.57	2.57	7997.23	13.39
	0.1	0.77	0.00	231.02	2.77	7887.38	14.88
	0.2	0.77	0.00	232.97	2.86	7845.88	14.80
	0.3	0.77	0.00	232.63	2.78	7810.96	14.37
	0.4	0.76	0.00	249.03	2.87	7648.97	12.69
	0.5	0.76	0.00	251.85	3.07	7579.82	14.15
	0.6	0.75	0.00	272.60	3.17	7390.71	15.27
	0.7	0.75	0.00	289.25	3.20	7255.63	16.79
	0.8	0.74	0.00	306.13	3.13	7166.44	15.83
	0.9	0.74	0.00	326.99	2.70	7101.36	13.75
	1	0.73	0.00	360.43	3.89	7099.71	13.52
K20H05d3	0	1.00	0.00	168.33	3.24	10358.03	18.95
	0.1	0.99	0.00	173.98	3.26	10222.05	19.07

	0.2	0.99	0.00	174.83	3.16	10143.22	16.99
	0.3	0.99	0.00	177.44	3.09	10051.83	15.85
	0.4	0.99	0.00	185.09	3.20	9934.68	17.15
	0.5	0.99	0.00	190.32	3.33	9828.32	19.45
	0.6	0.99	0.00	206.97	3.63	9682.82	20.55
	0.7	0.98	0.00	215.58	3.90	9590.12	20.20
	0.8	0.98	0.00	225.83	3.83	9525.54	19.26
	0.9	0.98	0.00	236.11	3.52	9491.33	18.80
	1	0.98	0.00	275.85	2.41	9473.19	17.22
K20H10d1	0	0.52	0.00	268.82	3.21	5457.19	11.56
	0.1	0.52	0.00	270.09	3.09	5436.42	11.13
	0.2	0.52	0.00	258.21	2.99	5460.27	11.34
	0.3	0.52	0.00	276.32	3.52	5365.59	11.95
	0.4	0.52	0.00	266.84	3.42	5372.28	11.30
	0.5	0.52	0.00	293.98	3.82	5240.71	9.28
	0.6	0.52	0.00	307.89	3.95	5163.17	8.60
	0.7	0.51	0.00	342.48	4.51	5014.87	9.63
	0.8	0.50	0.00	389.73	5.84	4852.64	12.19
	0.9	0.50	0.00	436.06	4.87	4744.46	9.79
	1	0.49	0.00	519.62	7.75	4712.36	8.34
K20H10d2	0	0.77	0.00	243.86	2.54	7726.77	11.09
	0.1	0.77	0.00	242.09	2.63	7704.81	12.40
	0.2	0.77	0.00	240.77	2.62	7682.10	11.13
	0.3	0.76	0.00	248.87	2.60	7583.63	9.03
	0.4	0.76	0.00	247.06	2.68	7560.01	9.79
	0.5	0.76	0.00	259.64	2.71	7444.15	9.91
	0.6	0.76	0.00	270.60	2.86	7331.75	12.57
	0.7	0.75	0.00	289.28	3.35	7206.36	14.72
	0.8	0.74	0.00	304.69	3.35	7118.00	13.91
	0.9	0.74	0.00	321.41	3.07	7063.21	13.07
	1	0.73	0.00	356.69	4.31	7062.01	12.48
K20H10d3	0	0.99	0.00	157.95	1.51	10231.14	17.16
	0.1	0.99	0.00	156.50	1.50	10142.79	15.14
	0.2	0.99	0.00	158.45	1.49	10065.60	15.09
	0.3	0.99	0.00	161.69	1.52	9986.24	14.41
	0.4	0.99	0.00	164.02	1.43	9912.34	15.44
	0.5	0.99	0.00	173.44	1.69	9796.77	17.02
	0.6	0.98	0.00	189.17	2.79	9685.99	21.12
	0.7	0.98	0.00	209.68	3.82	9579.82	22.34
	0.8	0.98	0.00	221.04	3.73	9501.75	21.12
	0.9	0.98	0.00	248.56	2.28	9428.89	15.15
	1	0.98	0.00	271.47	2.38	9432.69	14.15

Table A.6: Average and standard error values of throughput, flow time and cost of scenarios with $K = 20$.