OmniaScience

Journal of Industrial Engineering and Management
JIEM, 2024 – 17(1): 275-291 – Online ISSN: 2013-0953 – Print ISSN: 2013-8423
https://doi.org/10.3926/jiem.6572

Optimization of the OEE Indicator Through Meta-Models' Simulation in the Buffer Allocation Problem

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Received: September 2023
Accepted: March 2024

Abstract:

Purpose: The buffer allocation problem (BAP) arises in the design of production systems; it involves analyzing and defining the optimal distribution of buffers within a production line. This paper presents a BAP formulation in a parallel series line from a cup sublimation process with unreliable operating conditions. The main objective of this study is to develop a new BAP solution proposal, considering the optimization of the OEE indicator used in Lean Manufacturing.

Design/methodology/approach: The BAP was analyzed under an optimization approach from two different criteria: firstly, the maximization of the OEE indicator (Overall Equipment Effectiveness) utilized in Lean Manufacturing, as well as the maximization of the average production rate (Throughput). The case study involves unreliable operating conditions. Process times, and timeframes between failures and repairs, consider normal distribution functions. The evaluation method employed in the study includes the use of simulation meta-models built from experiment designs and production line simulations; on the other hand, the nonlinear GRG algorithm is used to solve the mathematical models.

Findings: In the study carried out, it is shown that the OEE indicator can be affected when more buffers are allocated than necessary, hence it is important to calculate and establish the best configuration for them through an analysis such as the one proposed in this document.

Research limitations/implications: The research is limited to a case study of an unreliable production line from a cup sublimation process.

Practical implications: The proposed solution established in this study can be used in other production lines with configurations different from the one analyzed, considering the optimization criterion of the OEE indicator.

Originality/value: Seeking that the allocation of buffers within the production line improves the OEE indicator is something new in the literature, therefore, the results achieved in this research become even more relevant.

Keywords: buffer allocation problem, meta-models, simulation, OEE, throughput, GRG algorithm

To cite this article:

Hernández-Vázquez, J.I., Hernández-Vázquez, J.O., Hernández-González, S., & Olivares-Vera, D.A. (2024). Optimization of the OEE indicator through meta-models' simulation in the buffer allocation problem. *Journal of Industrial Engineering and Management*, 17(1), 275-291. https://doi.org/10.3926/jiem.6572

1. Introduction

The buffer allocation problem (BAP) arises in the design of production systems; it involves analyzing and defining the optimal distribution of buffers within a production line. The main reason for maintaining buffers is to allow workstations to operate independently from each other. Buffers have a significant impact on improving the efficiency of the production line by eliminating detrimental effects due to failures or variations in processing times (Hernández-Vázquez, Hernández-González, Hernández-Vázquez, Jiménez-García & Hernández-Ripalda, 2022a; Hoe, Prakash, Kamaruddin & Seng, 2019; Kose & Kilincci, 2020). On the other hand, they can increase the system maintenance cost and decrease its profitability. Thus; finding the optimal buffer capacities that result in a satisfactory process is a major problem in production systems research (Motlagh, Azimi, Amiri & Madraki, 2019).

In recent years, a significant number of companies have opted for the implementation of Lean Manufacturing, to improve their production processes and generate greater profits, by eliminating or reducing everything that does not add value to the products, but add cost and work (Hernández-Vázquez, Hernández-González, Hernández-Vázquez, Jiménez-García & Baltazar-Flores, 2021; Socconini, 2019).

This study presents a new BAP solution proposal as its main contribution, considering the optimization of the OEE indicator used in Lean Manufacturing. This indicator represents the time that is actually worked, without downtime, at the established capacity, and without defects (Socconini, 2019). The search for the allocation of buffers within the production line to improve OEE is something new in the literature, for which the results achieved in this research become yet more relevant. In addition, a second analysis of the problem is carried out taking into consideration the optimization of the throughput, in order to compare the allocation of buffers between the two optimization criteria.

It is important to mention that this work considers the analysis of a real case study from a company that is dedicated to the sublimation of cups; for this reason, the results achieved have a practical approach within a production line, whose operating conditions are considered unreliable, since there are downtimes due to machine breakdowns, repair time, as well as quality issues.

Another aspect to highlight is the evaluation method used. Like in other works (Amiri & Mohtashami, 2012; Hernández-Vázquez et al., 2022a; Mohtashami, 2014), meta-models built from experimental designs and simulations of the production line are used. The simulation software used for this work is PROMODEL; this was designed to analyze manufacturing processes of one or more products, assembly and transformation lines, among others (García-Dunna, García-Reyes & Cárdenas-Barrón, 2013). The use of such software in the analysis of the BAP has been previously reported in another work (Hernández-Vázquez et al., 2022a). On the other hand, the nonlinear GRG algorithm is used in the search for the solution as an optimization method.

The rest of this document is organized as follows: Section 2 explains the formulation of the BAP as well as the mathematical models considered. Section 3 then describes the case study. Section 4 illustrates the meta-models developed. The optimization method used is described later in section 5. Section 6 details the numerical results obtained. Finally, a section of conclusions is presented where the scope of the results generated is addressed.

2. Buffer Allocation Problem

The buffer allocation problem is classified as an NP-Hard combinatorial optimization problem in the design of production lines (Demir, Tunali & Eliiyi, 2014; Weiss, Schwarz & Stolletz, 2019). This consists of defining the allocation of storage places (buffers) within a production line, with the objective of maximizing the efficiency of the process.

Currently, there is a great diversity of studies reported in the literature that address BAP under different optimization criteria. Mentioned below are some of the most outstanding works:

The most common optimization criteria consider maximizing the average throughput rate (Gao, 2022; Gao, Higashi, Kobayashi, Taneda, Rubrico & Ota, 2020; Gao & Liu, 2023; Kassoul, Cheikhrouhou & Zufferey, 2023; Köse, Demir, Tunal & Eliiyi, 2015; Kose & Kilincci, 2015; Koyuncuoğlu & Demir, 2021; Lin & Chiu, 2018; Nahas, Nourelfath & Gendreau, 2014; Narasimhamu, Reddy & Rao, 2014; Patchong & Kerbache, 2017; Wang, Song, Shin & Moon, 2014), minimizing the total buffer size (Li, 2013; Weiss & Stolletz, 2015), minimizing the total cost of allocation (Magnanini, Terkaj & Tolio, 2022; Nahas, 2017; Nahas & Nourelfath, 2018; Ouzineb, Mhada, Pellerin & El Hallaoui, 2018; Tiacci, 2022), among others (Alfieri, Matta & Pastore, 2020; Hernández-Vázquez, Hernández-González, Jiménez-García, Hernández-Ripalda & Hernández-Vázquez, 2019; Hernández-Vázquez, Hernández-González, Hernández-Vázquez, Figueroa-Fernández & Cancino de la Fuente, 2022b; Koyuncuoğlu & Demir, 2023; Shaaban & Romero-Silva, 2021; Shao, Moroni, Li, & Xu, 2022; Xi, Smith, Chen, Mao, Zhang & Yu, 2021; Zhou, Liu, Yu & Tao, 2018).

2.1. Formulation

In this study, the BAP is analyzed under a single-objective optimization approach, for which two different criteria were considered. The first aims to maximize the value of the OEE indicator, and the second aims to maximize the throughput (products/minute).

Four mathematical models were generated. The first two aim at optimizing the OEE, while the third and fourth seek to optimize the throughput. Each of them is described in detail below:

2.2. Mathematical Model 1

The first mathematical model aims to maximize the OEE indicator of the production line, for a certain number of buffers.

Find $B=(B_1,B_2,\ldots,B_n)$ in order to

$$Max\ Z_1 = OEE(B) \tag{1}$$

Subject to

$$B_i \leq U_i \qquad \forall i = 1 \text{ to } n \tag{2}$$

$$B_i \geq L_i \qquad \forall i = 1 \text{ to } n \tag{3}$$

$$\sum B_i = N \tag{4}$$

$$B_i \geq 0 \text{ and integers} \tag{5}$$

Where:

B_i = Decision variable or number of buffers in the buffer locations i
n = Number of buffer locations
$OEE(B)$ = OEE of production line
L_i = Lower limit of B_i
U_i = Upper limit or capacity of B_i
N = Number of buffers available

It is important to note that $OEE(B)$ is a regression meta-model that is generated through the design of experiments (DOE) and simulation. Section 4, "Meta-modelos", describes the mode on how each of these were obtained.

The first mathematical model contemplates constraints (2, 3, and 4) that are related to the number of buffers in each buffer location. Due to production space limitations, buffer locations cannot register an allocation greater than their capacity.

2.3. Mathematical Model 2

The second mathematical model is distinguished from the first by the constraint (9) where the allocation of all available buffers is not mandatory (soft constraint).

$$Max\ Z_1 = OEE(B) \tag{6}$$

Subject to

$$B_i \leq U_i \qquad \forall i = 1 \text{ to } n \tag{7}$$

$$B_i \geq L_i \qquad \forall i = 1 \text{ to } n \tag{8}$$

$$\sum B_i \leq N \tag{9}$$

$$B_i \geq 0 \text{ and integers} \tag{10}$$

2.4. Mathematical Model 3

The third mathematical model aims to maximize the throughput of the line (products manufactured per unit of time), for a given number of buffers.

Find $B = (B_1, B_2, \ldots, B_n)$ in order to

$$Max\ Z_2 = TH(B) \tag{11}$$

Subject to

$$B_i \leq U_i \qquad \forall i = 1 \text{ to } n \tag{12}$$

$$B_i \geq L_i \qquad \forall i = 1 \text{ to } n \tag{13}$$

$$\sum B_i = N \tag{14}$$

$$B_i \geq 0 \text{ and integers} \tag{15}$$

Where:

$TH(B)$ = Throughput of the line, based on the spaces allocated in front of line B

2.5. Mathematical Model 4

The fourth mathematical model is similar to the third. It differs from this one in constraint (19) where the allocation of all available buffers is not mandatory (soft constraint).

$$Max\ Z_2 = TH(B) \tag{16}$$

Subject to:

$$B_i \leq U_i \qquad \forall i = 1 \text{ to } n \tag{17}$$

$$B_i \geq L_i \qquad \forall i = 1 \text{ to } n \tag{18}$$

$$\sum B_i \leq N \tag{19}$$

$$B_i \geq 0 \text{ and integers} \tag{20}$$

3. Case Study

As a case study, a real rate sublimation process was considered, which has an unreliable production line behavior (with stoppages and repairs), whose process consists of 10 different workstations (from A to J) where the different operations are performed, in addition there are 6 buffer locations within the process. Table 1 describes the operations carried out at each station, as well as the number of operators or machines.

Station	Operation	Number of workers or machines
A	Clean cup	1
B	Print design	1
C	Cut out	1
D	Place paper in cup	1
E	Press sublimation paper into cup	2
F	Sublimate cooling	1
G	Remove paper from cup	1
H	Assemble packaging	1
I	Individually package cup	1
J	Assemble production batches	1

Table 1. Operations performed at each station

Figure 1 shows the structure of the production line. The circles indicate the stations, the triangles represent the buffer locations of the in-process inventory, and the square points to the quality inspector. The raw material enters the production line at different stations and follows a flow marked in the process. Station D assembles the outputs of stations A and C (assembly 1); station I assembles the outputs of stations H and G (assembly 2). Finally, station J performs the last operation of the process to generate a finished product.

The production line includes a quality inspector, who can classify the inventory in process into one of the following categories:

- Rejection: The product has serious inconsistencies that cannot be reprocessed and therefore must be rejected.
- Compliant: The product does not present inconsistencies and must follow the sequence of the original process.

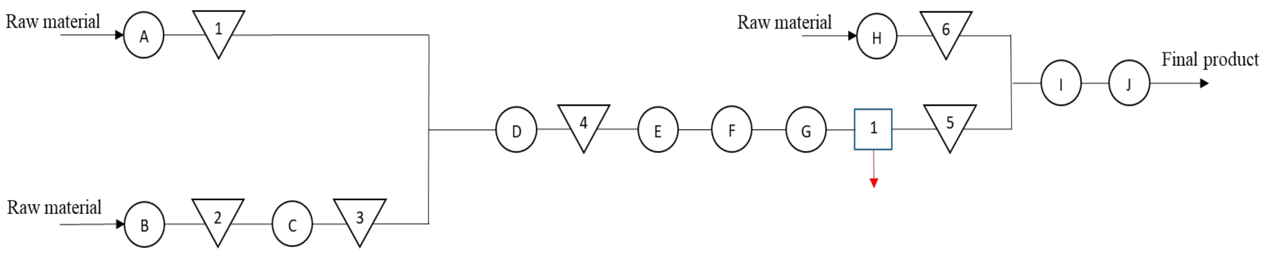

Figure 1. Production line

Table 2 presents the process times, times between failures and repair times that exist in the case study, considering a Normal distribution (N). Table 3 indicates the inspection times and the probabilities of classifying the inventory in process in any of the categories mentioned above.

The upper limit of the buffer locations (decision variables) was set with a value of 50 places for the parts. With regard to the lower limit, this study contemplates the value of a space or place, ensuring that a minimum capacity is maintained in any location analyzed.

Station	Processing time (Seconds)	Time between failures (minutes)	Time to repair (minutes)
A	N (5.75,1)	–	–
B	N(85.5,5)	N(150,10)	N (10,0.2)
C	N(60,5)	–	–
D	N(65.55,5)	–	–
E	N(163.88,5)	N(120,10)	N (10,0.2)
F	N(120,5)	–	–
G	N(10.93,1)	–	–
H	N(50,3)	–	–
I	N(10,2)	–	–
J	N(30,4)	–	–

Table 2. Process, failure-to-failure and repair times for each station

Inspector	Processing time (Seconds)	Probability	
		Rejection	Conform
1	N (10,2)	5%	95%

Table 3. Inspection times and classification probabilities

4. Meta-Models

A simulation model is a representation of a real-world system, while meta-models (referenced in this paper) are a mathematical approximation of a simulation model (Kleijnen & Sargent, 2000). Meta-models are developed to obtain a better understanding of the relationship between the input variables and the output variables of the system under study (Noguera & Watson, 2006).

In this research, two polynomial regression meta-models were developed; this category of meta-models has provided outstanding results in simulation work (Amiri & Mohtashami, 2012; Dengiz & Akbay, 2000; Durieux & Pierreval, 2004; Hernández-Vázquez et al., 2022a). The methodology used for its elaboration is established by Amiri and Mohtashami (2012). It employs design of experiments (DOE) and the simulation to fit a meta-model to the average rate of production as a response (y), considering buffer locations as factors (x_i). It should be noted that unlike what was done by Amiri and Mohtashami (2012), the OEE indicator is considered as a response (y) in the first meta-model generated in this study. The calculation of the OEE indicator results from the multiplication of three factors; availability, performance and quality, which is described in detail by Socconini (2019).

A complete factorial design 2^6 was carried out, with which 64 combinations were generated. Each of the 64 combinations of the experiment was simulated in the PROMODEL software in order to analyze the results of the response (OEE and throughput). The study considered 10 replications for each combination (that is to say, 640 simulations). The simulation time was 8 hours for each replica with a warm-up time of 2 hours. The PC where these simulations were performed includes an AMD Ryzen 3 4300U processor with Radeon Graphics 2.70 GHz and 8GB of RAM.

Regression meta-models involving the main effects and their interactions between two factors were generated. The Anova analysis of each of them is presented in Table 4. The Fisher test demonstrates a high degree of significance and each meta-model is able to satisfactorily explain the variability in the variable response. The comparison of the results obtained with the meta-models and the simulation is another way to evaluate the validity of these; the approach suggested by Durieux and Pierreval (2004) and Amiri and Mohtashami (2012) was used. From the experimental design, fifteen combinations of values in the decision variables were randomly selected; the average absolute error turned out to be less than the 6% established by Durieux and Pierreval (2004). Therefore, these are considered to be sufficiently accurate (see Table 5).

Table 6 presents the meta-models developed for the case study, which estimates the value of the OEE indicator and the throughput (products/min) when evaluating the buffers allocated in the different buffer locations (from B_1 to B_6).

OEE						
Source	**df**	**SS**	**MS**	**F Value**	**P Value**	
Model	21	5.74E-03	2.73E-04	8.0259	< 0.0001	Significant
Main effects	6	2.83E-03	2.83E-03	83.0811		
Interaction 2 factors	15	2.91E-03	2.91E-03	85.4625		
Residual	42	1.43E-03	3.41E-05			
Cor total	63					
R-Squared	80%					
Throughput						
Source	**df**	**SS**	**MS**	**F Value**	**P Value**	
Model	21	4.64E-03	2.21E-04	10.9500	< 0.0001	Significant
Main effects	6	2.51E-03	2.51E-03	124.6263		
Interaction 2 factors	15	2.12E-03	2.12E-03	105.3595		
Residual	42	8.47E-04	2.02E-05			
Cor total	63					
R-Squared	85%					

Table 4. Anova analysis

	Combination	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Average absolute error (%)
	B_1	50	50	1	50	1	1	50	50	1	1	26	17	48	4	21	
	B_2	1	50	50	1	1	1	1	50	50	1	20	35	32	24	44	
	B_3	1	50	50	50	50	1	1	50	50	50	30	21	22	17	33	
	B_4	1	1	50	1	50	1	50	50	1	50	40	33	34	38	15	
	B_5	1	1	1	50	50	1	1	1	50	50	12	47	44	46	38	
	B_6	1	1	1	1	1	50	50	50	50	50	11	23	18	13	6	
OEE	Simulation	70.798%	74.293%	74.060%	74.293%	74.060%	71.095%	74.347%	74.347%	74.225%	74.704%	73.407%	74.512%	73.694%	74.521%	73.390%	
	Meta-model	71.539%	74.685%	73.813%	74.026%	74.727%	71.743%	74.100%	73.909%	74.606%	74.939%	73.975%	74.105%	73.943%	73.982%	74.218%	
	Absolute error	1.0473%	0.5274%	0.3333%	0.3603%	0.9010%	0.9112%	0.3320%	0.5888%	0.5127%	0.3144%	0.7735%	0.5469%	0.3369%	0.7233%	1.1283%	0.6225%
Throughput	Simulation	0.6123	0.6404	0.6406	0.6404	0.6406	0.6098	0.6413	0.6413	0.6402	0.6446	0.6406	0.6433	0.6394	0.6425	0.6354	
	Meta-model	0.6186	0.6445	0.6382	0.6378	0.6450	0.6174	0.6388	0.6390	0.6441	0.6470	0.6405	0.6402	0.6397	0.6395	0.6408	
	Absolute error	1.0335%	0.6344%	0.3780%	0.4087%	0.6768%	1.2427%	0.3777%	0.3574%	0.6102%	0.3676%	0.0246%	0.4878%	0.0475%	0.4692%	0.8499%	0.5311%

Table 5. Meta-model validation

Meta-model OEE	Meta-model Throughput
***OEE*(*B*) =**	***TH*(*B*) =**
+0.714989037	+0.616993907
-1.91734E-05**B*1	+9.22E-06**B*1
+0.000429582**B*2	+0.000416759**B*2
+0.000537695**B*3	+0.000412529**B*3
+0.000419784**B*4	+0.000414817**B*4
-2.36387E-06**B*5	+2.82E-06**B*5
+2.04199E-05**B*6	-1.78E-05**B*6
-1.55702E-08**B*1**B*2	-8.68E-08**B*1**B*2
-3.6353E-07**B*1**B*3	-1.52E-07**B*1**B*3
-1.11956E-06**B*1**B*4	+1.30E-07**B*1**B*4
+5.25055E-07**B*1**B*5	-5.42E-08**B*1**B*5
+5.01946E-07**B*1**B*6	-8.24E-07**B*1**B*6
-5.7358E-06**B*2**B*3	-5.47E-06**B*2**B*3
-6.64169E-06**B*2**B*4	-5.57E-06**B*2**B*4
+5.25055E-07**B*2**B*5	-5.42E-08**B*2**B*5
+4.63257E-07**B*2**B*6	+1.95E-07**B*2**B*6
-6.11587E-06**B*3**B*4	-5.38E-06**B*3**B*4
-4.52945E-07**B*3**B*5	-5.42E-08**B*3**B*5
-1.60226E-06**B*3**B*6	+4.34E-08**B*3**B*6
+4.52945E-07**B*4**B*5	+5.42E-08**B*4**B*5
+2.49311E-06**B*4**B*6	+1.19E-06**B*4**B*6
-4.52945E-07**B*5**B*6	-5.42E-08**B*5**B*6

Table 6. Meta-models developed for the case study

5. Optimization Method

To solve the mathematical models, the GRG algorithm was used. This is a nonlinear optimization algorithm developed by Leon Lasdon, from the University of Texas (in Austin), and by Allan Waren from Cleveland University. The GRG solver uses two techniques for determining the search direction. The default option is the Quasi-Newton method, a gradient-based technique; The second option is the conjugated gradient method. Depending on the available storage, the GRG solver can automatically switch between the Quasi-Newton method or the conjugated gradient method (Muzzammil, Alam & Zakwan, 2015; Smith & Lasdon, 1992).

6. Numerical Results

This section describes the results generated by solving the mathematical models in section 2, which are aimed at optimizing the value of the OEE indicator and the throughput.

6.1. Optimization of the OEE Indicator

30 scenarios of the first mathematical model were solved, which aims to maximize the OEE indicator, as well as the mandatory allocation of all available buffers; It starts with 10 places and 10-unit increases were made in the total number of buffers available on the line until 300 places were reached. In each scenario, the optimal allocation of available places or spaces was found using the LINGO V13 package; Although it is a nonlinear integer mixed model, the execution time is reasonable so at the moment, the use of a metaheuristic technique is not justified.

Table 7 shows the different configurations of buffers allocated and the OEE value achieved in each test: in scenarios 1 to 20 it is observed that the optimal allocation is destining the buffers to buffer locations 3, 4, 6, and 5, filling them gradually and with a pattern of arrangement similar to a bell; Subsequently, from scenario 21 the accommodation gives preference to the buffer locations at the ends. In this sense, the result agrees with what was previously observed where the non-uniform allocation of places gives good results.

Figure 2 shows the behavior of the OEE indicator as the buffers were allocated in each of the tests.

Test	N	Buffer locations						OEE
		B_1	B_2	B_3	B_4	B_5	B_6	
1	10	1	1	5	1	1	1	71.8451%
2	20	1	1	15	1	1	1	72.3685%
3	30	1	1	25	1	1	1	72.8920%
4	40	1	1	35	1	1	1	73.4154%
5	50	1	1	45	1	1	1	73.9388%
6	60	1	1	50	6	1	1	74.2551%
7	70	1	1	50	16	1	1	74.3643%
8	80	1	1	50	26	1	1	74.4735%
9	90	1	1	50	36	1	1	74.5826%
10	100	1	1	50	46	1	1	74.6918%
11	110	1	1	50	50	1	7	74.7748%
12	120	1	1	50	50	1	17	74.8402%
13	130	1	1	50	50	1	27	74.9057%
14	140	1	1	50	50	1	37	74.9712%
15	150	1	1	50	50	1	47	75.0367%
16	160	1	1	50	50	8	50	75.0395%
17	170	1	1	50	50	18	50	75.0156%
18	180	1	1	50	50	28	50	74.9916%
19	190	1	1	50	50	38	50	74.9677%
20	200	1	1	50	50	48	50	74.9437%
21	210	9	50	1	50	50	50	75.0077%
22	220	19	50	1	50	50	50	74.9828%
23	230	29	50	1	50	50	50	74.9578%
24	240	39	50	1	50	50	50	74.9329%
25	250	49	50	1	50	50	50	74.9080%
26	260	50	50	10	50	50	50	74.7472%
27	270	50	50	20	50	50	50	74.5714%
28	280	50	50	30	50	50	50	74.3956%
29	290	50	50	40	50	50	50	74.2197%
30	300	50	50	50	50	50	50	74.0439%
Total	**4650**	415	520	1030	1135	655	895	
% allocation		8.92%	11.18%	22.15%	24.41%	14.09%	19.25%	

Table 7. Solutions generated with the first mathematical model

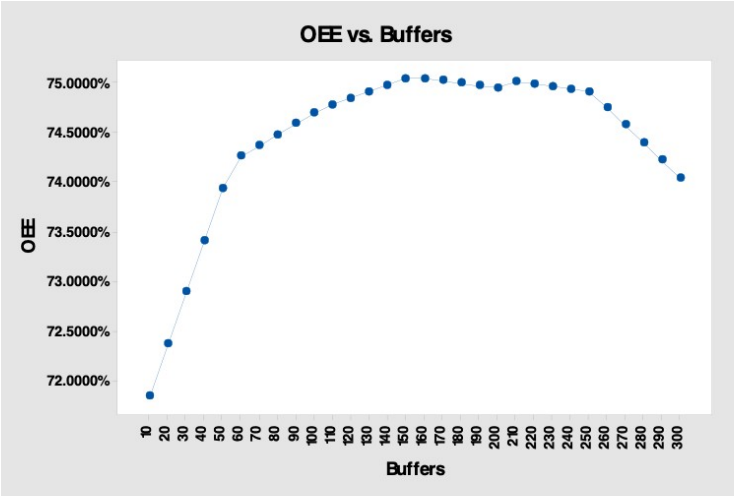

Figure 2. OEE Vs Buffers

Buffer locations						Total allocated buffers	OEE
B_1	B_2	B_3	B_4	B_5	B_6		
1	1	50	50	1	50	153	75.0563%

Table 8. Solution to the second mathematical model

It is interesting to mention that a maximum OEE value is reached when there are 160 places available, later as more buffers are allocated the value of the OEE indicator decreases, having as a relevant finding in this study: in this process the OEE indicator is affected as more buffers are added than necessary in the production line, in other words, allocating more than 160 places will not improve the OEE indicator, even if these places are optimally distributed.

Table 8 illustrates the buffer allocation solution generated to the second mathematical model, which aims to optimize the OEE indicator, but the allocation of all available buffers is not mandatory. A number of 300 available buffers was contemplated, equaling the maximum number considered for the first model. The result that maximizes the OEE indicator considers the allocation of 153 buffers.

6.2. Optimization of the Throughput

30 scenarios of the third mathematical model were solved, which aims to optimize the throughput, as well as the mandatory allocation of all available buffers; It starts with 10 places and 10-unit increases were made in the total number of buffers available on the line until 300 places were reached. In each scenario, the optimal allocation of available places or spaces was found using the LINGO V13 package; Although it is a nonlinear integer mixed model, the execution time is reasonable so at the moment, the use of a metaheuristic technique is not justified.

Table 9 shows the different buffer configurations allocated and the value of the throughput (products/minute) achieved in each test.

Figure 3 shows the graphical behavior of the throughput as the buffers were allocated in each of the tests. It is important to note that this reaches its peak in test 16 as happened with the OEE indicator in the first mathematical model.

Table 10 illustrates the buffer allocation solution generated to the fourth mathematical model, which aims to optimize the throughput, but the allocation of all available buffers is not mandatory. A number of 300 available buffers was contemplated, equaling the maximum number considered for the third model. The result that maximizes the throughput considers the allocation of 153 buffers.

Test	N	Buffer locations						Throughput
		B_1	B_2	B_3	B_4	B_5	B_6	
1	10	1	5	1	1	1	1	0.619839
2	20	1	15	1	1	1	1	0.623897
3	30	1	25	1	1	1	1	0.627955
4	40	1	35	1	1	1	1	0.632012
5	50	1	45	1	1	1	1	0.636070
6	60	1	50	6	1	1	1	0.638767
7	70	1	50	16	1	1	1	0.640104
8	80	1	50	26	1	1	1	0.641441
9	90	1	50	36	1	1	1	0.642777
10	100	1	50	46	1	1	1	0.644114
11	110	1	50	1	50	1	7	0.644875
12	120	1	50	1	50	1	17	0.645382
13	130	1	1	50	50	1	27	0.645957
14	140	1	1	50	50	1	37	0.646390
15	150	1	1	50	50	1	47	0.646823
16	160	1	1	50	50	8	50	0.646953
17	170	1	1	50	50	18	50	0.646953
18	180	1	1	50	50	28	50	0.646953
19	190	1	1	50	50	38	50	0.646953
20	200	1	1	50	50	48	50	0.646953
21	210	9	1	50	50	50	50	0.646666
22	220	19	1	50	50	50	50	0.646307
23	230	29	1	50	50	50	50	0.645949
24	240	39	1	50	50	50	50	0.645590
25	250	49	1	50	50	50	50	0.645231
26	260	50	10	50	50	50	50	0.644002
27	270	50	20	50	50	50	50	0.642676
28	280	50	30	50	50	50	50	0.641350
29	290	50	40	50	50	50	50	0.640024
30	300	50	50	50	50	50	50	0.638698
Total	**4650**	415	638	1037	1010	655	895	
% allocation		8.92%	13.72%	22.30%	21.72%	14.09%	19.25%	

Table 9. Solutions generated with the third mathematical model

Buffer locations						Total allocated buffers	Throughput
B_1	B_2	B_3	B_4	B_5	B_6		
1	50	1	50	1	50	153	0.647057

Table 10. Solution to the fourth mathematical model

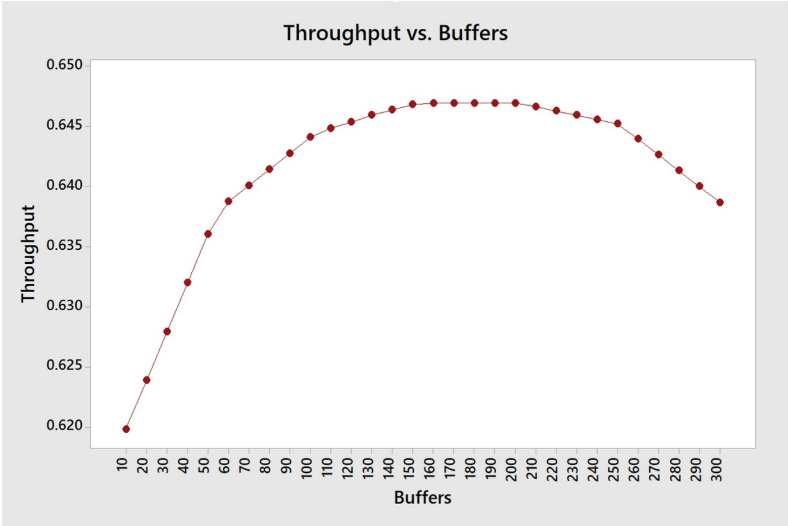

Figure 3. Throughput Vs Buffers

6.3. OEE vs Throughput Comparison

Figure 4 shows a comparative graph of the total percentage of buffers allocated in the 30 tests, between mathematical models one and three. For the case study presented, the percentage buffers allocated to maximize the OEE indicator was very similar to those obtained in the maximization of the throughput, distinguishing only buffer locations 2, 3 and 4.

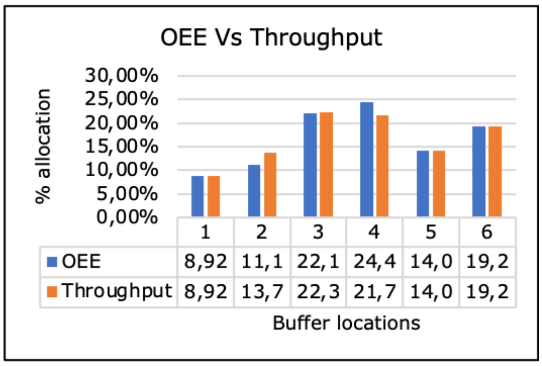

Figure 4. OEE Vs Throughput

Table 8 and 10 establish the assigned buffers that maximize the OEE and throughput of the case study, generated by mathematical models two and four respectively. In both cases the number of buffers generated by the best solution was 153, however, there is a difference between buffer locations 2 and 3, since for the OEE, 1 and 50 buffers must be allocated respectively, while for the throughput, these values are reversed. Table 11 shows a comparison between these two assignments, in addition, the OEE and throughput values that are generated in each meta-model are also shown.

Mathematical model	Buffer locations						Total allocated buffers	Meta-model OEE	Meta-model Throughput
	B_1	B_2	B_3	B_4	B_5	B_6			
2	1	1	50	50	1	50	153	**75.0563%**	0.646953
4	1	50	1	50	1	50	153	74.9102%	**0.647057**

Table 11. Comparison of buffers allocated between mathematical models two and three

Table 12 summarizes the behavior of the OEE indicator and the throughput in each of the tests, as well as the best solution (153 buffers) obtained through the mathematical models. The clarity in the upward and downward behavior in the OEE values due to the allocation of buffers is a benefit achieved through the use of the mathematical models proposed in this study.

Test	Total allocated buffers	OEE		Throughput	
		Mathematical model 1	Mathematical model 2	Mathematical model 3	Mathematical model 4
1	10	71.8451%		0.619839	
2	20	72.3685%		0.623897	
3	30	72.8920%		0.627955	
4	40	73.4154%		0.632012	
5	50	73.9388%		0.636070	
6	60	74.2551%		0.638767	
7	70	74.3643%		0.640104	
8	80	74.4735%		0.641441	
9	90	74.5826%		0.642777	
10	100	74.6918%		0.644114	
11	110	74.7748%		0.644875	
12	120	74.8402%		0.645382	
13	130	74.9057%		0.645957	
14	140	74.9712%		0.646390	
15	150	75.0367%		0.646823	
Best solution	153		**75.0563%**		**0.647057**
16	160	75.0395%		0.646953	
17	170	75.0156%		0.646953	
18	180	74.9916%		0.646953	
19	190	74.9677%		0.646953	
20	200	74.9437%		0.646953	
21	210	75.0077%		0.646666	
22	220	74.9828%		0.646307	
23	230	74.9578%		0.645949	
24	240	74.9329%		0.645590	
25	250	74.9080%		0.645231	
26	260	74.7472%		0.644002	
27	270	74.5714%		0.642676	
28	280	74.3956%		0.641350	
29	290	74.2197%		0.640024	
30	300	74.0439%		0.638698	

Table 12. Summary of the results obtained through the mathematical models

7. Conclusions

This work presented as main contribution a new proposal for a BAP solution, considering as an optimization criterion the OEE indicator used in Lean Manufacturing. A sublimation process whose structure is that of a parallel production line in series, with unreliable operating conditions, was taken as a case study.

The BAP was analyzed under a single-objective optimization approach, for which two different criteria were considered: first, the maximization of the OEE indicator and as a second criterion, the maximization of the throughput.

The evaluation method used considered two meta-models built from designs of experiments (DOE) and simulations of the production line through the use of PROMODEL software. The first of them reflected the behavior of the OEE indicator, while the second represented the fluctuations in the throughput.

In the study carried out, it was shown that the OEE indicator can be affected when more buffers are allocated than necessary, so it is important to calculate and establish the best configuration of these through an analysis such as the one proposed in this document.

Another relevant finding of this research was that the number of buffers used to maximize the OEE indicator was the same as that obtained to maximize the throughput, however, the accommodation configurations of these were different.

From the administrative point of view this is relevant since the OEE indicator is frequently used to plan and manage the performance of production lines; at least in this case study it was observed that there are a number of places on the line where the OEE indicator reaches a maximum value, beyond this critical value, the indicator begins to deteriorate.

Unlike other studies where simulation is used as an evaluation method, the use of meta-models facilitated and streamlined the measurement of optimization objectives, allowing solutions to be achieved efficiently with the GRG algorithm. The implementation of meta-models helps in the analysis of complex production systems, taking advantage of one of the main virtues of simulation, and allows optimization methods to significantly improve their computational efficiency, since they behave as an analytical evaluation procedure (Hernández-Vázquez et al., 2022a).

The mathematical models 1 and 2 presented in this document allow finding the best buffer configurations that optimize the OEE indicator; the meta-models developed for the case study analyzed facilitate the evaluation of this indicator. In future cases of application, it is suggested to use these mathematical models for the analysis of other production lines whose optimization objective is the same as the one evaluated in this study.

Finally, for future research it is recommended to use as an optimization criterion the OEE indicator for the allocation of buffers and make a comparison with other different criteria, such as minimizing the total size of the buffer or minimizing the total cost of the allocation, to see the differences or similarities between them. In addition, it would be relevant to analyze production lines with other types of configurations to evaluate the impact on the OEE indicator.

Declaration of Conflicting Interests

The authors declare that there is no conflict of interest with respect to the research, authorship, or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

References

Alfieri, A., Matta, A., & Pastore, E. (2020). The time buffer approximated Buffer Allocation Problem: A row–column generation approach. *Computers and Operations Research*, 115, 104835. https://doi.org/10.1016/j.cor.2019.104835

Amiri, M., & Mohtashami, A. (2012). Buffer allocation in unreliable production lines based on design of experiments, simulation, and genetic algorithm. *International Journal of Advanced Manufacturing Technology*, 62(1–4), 371-383. https://doi.org/10.1007/s00170-011-3802-8

Demir, L., Tunali, S., & Eliiyi, D.T. (2014). The state of the art on buffer allocation problem: A comprehensive survey. *Journal of Intelligent Manufacturing*, 25(3), 371-392. https://doi.org/10.1007/s10845-012-0687-9

Dengiz, B., & Akbay, K.S. (2000). Computer simulation of a PCB production line: Metamodeling approach. *International Journal of Production Economics,* 63(2), 195-205. https://doi.org/10.1016/S0925-5273(99)00013-4

Durieux, S., & Pierreval, H. (2004). Regression metamodeling for the design of automated manufacturing system composed of parallel machines sharing a material handling resource. *International Journal of Production Economics,* 89(1), 21-30. https://doi.org/10.1016/S0925-5273(03)00199-3

Gao, S. (2022). A Bottleneck Detection-Based Tabu Search Algorithm for the Buffer Allocation Problem in Manufacturing Systems. *IEEE Access*, 10, 60507-60520. https://doi.org/10.1109/ACCESS.2022.3181134

Gao, S., Higashi, T., Kobayashi, T., Taneda, K., Rubrico, J.I.U., & Ota, J. (2020). Buffer allocation via Bottleneck-based variable neighborhood search. *Applied Sciences (Switzerland)*, 10(23). https://doi.org/10.3390/app10238569

Gao, S., & Liu, H. (2023). A data-driven ensemble algorithm of black widow optimizer and simulated annealing algorithms for multi-objective buffer allocation in production lines. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 0(0). https://doi.org/10.1177/09544054231157153

García-Dunna, E., García-Reyes, H., & Cárdenas-Barrón, L.E. (2013). *Simulación y análisis de sistemas con ProModel (Segunda ed.).* México: Pearson.

Hernández-Vázquez, J.I., Hernández-González, S., Hernández-Vázquez, J.O., Jiménez-García, J.A., & Baltazar-Flores, M.D.R. (2021). Production planning through lean manufacturing and mixed integer linear programming. *Leather and Footwear Journal*, 21(1), 47-62. https://doi.org/10.24264/lfj.21.1.5

Hernández-Vázquez, J.O., Hernández-González, S., Hernández-Vázquez, J.I., Jiménez-García, J.A., & Hernández-Ripalda, M. D. (2022a). Análisis multi-objetivo del problema de asignación del buffer con meta-modelos de simulación y una metaheurística híbrida. *Revista Iberoamericana de Automática e Informática Industrial*, 19(2), 221-232. https://doi.org/10.4995/riai.2021.15731

Hernández-Vázquez, J.O., Hernández-González, S., Hernández-Vázquez, J.I., Figueroa-Fernández, V., & Cancino de la Fuente, C.I. (2022b). Buffer allocation problem in a shoe manufacturing line: A metamodeling approach. *Revista Facultad de Ingenieria*, 103, 164-174. https://doi.org/10.17533/udea.redin.20210735

Hernández-Vázquez, J.O., Hernández-González, S., Jiménez-García, J.A., Hernández-Ripalda, M.D., & Hernández-Vázquez, J.I. (2019). Enfoque híbrido metaheurístico AG-RS para el problema de asignación del buffer que minimiza el inventario en proceso en líneas de producción abiertas en serie. *Revista Iberoamericana de Automática e Informática Industrial*, 16(4), 447-458. https://doi.org/10.4995/riai.2019.10883

Hoe, H.K., Prakash, J., Kamaruddin, S., & Seng, O.K. (2019). An integrated model for adjustment of process parameters to recover throughput shortage in semiconductor assembly: A Case Study. *Journal of Industrial Engineering and Management*, 12(2), 340-355. https://doi.org/10.3926/jiem.2742

Kassoul, K., Cheikhrouhou, N., & Zufferey, N. (2023). Simultaneous allocation of buffer capacities and service times in unreliable production lines. *International Journal of Production Research*, 1-21. https://doi.org/10.1080/00207543.2023.2168310

Kleijnen, J.P.C., & Sargent, R.G. (2000). A methodology for fitting and validating metamodels in simulation. *European Journal of Operational Research,* 120(1), 14-29. https://doi.org/10.1016/S0377-2217(98)00392-0

Köse, S.Y., Demir, L., Tunal, S., & Eliiyi, D.T. (2015). Capacity improvement using simulation optimization approaches: A case study in the thermotechnology industry. *Engineering Optimization*, 47(2), 149-164. https://doi.org/10.1080/0305215X.2013.875166

Kose, S.Y., & Kilincci, O. (2015). Hybrid approach for buffer allocation in open serial production lines. *Computers and Operations Research*, 60, 67-78. https://doi.org/10.1016/j.cor.2015.01.009

Kose, S.Y., & Kilincci, O. (2020). A multi-objective hybrid evolutionary approach for buffer allocation in open serial production lines. *Journal of Intelligent Manufacturing*, 31(1), 33-51. https://doi.org/10.1007/s10845-018-1435-6

Koyuncuoğlu, M.U., & Demir, L. (2021). Buffer capacity allocation in unreliable production lines: An adaptive large neighborhood search approach. *Engineering Science and Technology, an International Journal*, 24(2), 299-309. https://doi.org/10.1016/j.jestch.2020.08.012

Koyuncuoğlu, M.U., & Demir, L. (2023). An adaptive hybrid variable-large neighborhood search algorithm for profit maximization problem in designing production lines. *Computers & Industrial Engineering,* 175, 108871. https://doi.org/10.1016/j.cie.2022.108871

Li, J. (2013). Continuous improvement at Toyota manufacturing plant: Applications of production systems engineering methods. *International Journal of Production Research*, 51(23-24), 7235-7249. https://doi.org/10.1080/00207543.2012.753166

Lin, J.T., & Chiu, C.C. (2018). A hybrid particle swarm optimization with local search for stochastic resource allocation problem. *Journal of Intelligent Manufacturing*, 29(3), 481-495. https://doi.org/10.1007/s10845-015-1124-7

Magnanini, M.C., Terkaj, W., & Tolio, T.A.M. (2022). A novel algorithm for optimal buffer allocation in automated asynchronous unreliable lines. *International Journal of Advanced Manufacturing Technology*, 122, 4405-4419. https://doi.org/10.1007/s00170-022-09867-w

Mohtashami, A. (2014). A new hybrid method for buffer sizing and machine allocation in unreliable production and assembly lines with general distribution time-dependent parameters. *International Journal of Advanced Manufacturing Technology*, 74(9-12), 1577-1593. https://doi.org/10.1007/s00170-014-6098-7

Motlagh, M.M., Azimi, P., Amiri, M., & Madraki, G. (2019). An efficient simulation optimization methodology to solve a multi-objective problem in unreliable unbalanced production lines. *Expert Systems with Applications*, 138, 112836. https://doi.org/10.1016/j.eswa.2019.112836

Muzzammil, M., Alam, J., & Zakwan, M. (2015). An optimization technique for estimation of rating curve parameters. *National Symposium on Hydrology* (234-240).

Nahas, N. (2017). Buffer allocation and preventive maintenance optimization in unreliable production lines. *Journal of Intelligent Manufacturing*, 28(1), 85-93. https://doi.org/10.1007/s10845-014-0963-y

Nahas, N., & Nourelfath, M. (2018). Joint optimization of maintenance, buffers and machines in manufacturing lines. *Engineering Optimization*, 50(1), 37-54. https://doi.org/10.1080/0305215X.2017.1299716

Nahas, N., Nourelfath, M., & Gendreau, M. (2014). Selecting machines and buffers in unreliable assembly/disassembly manufacturing networks. *International Journal of Production Economics*, 154, 113-126. https://doi.org/10.1016/j.ijpe.2014.04.011

Narasimhamu, K.L., Reddy, V.V., & Rao, C.S.P. (2014). Optimal Buffer Allocation in Tandem Closed Queuing Network with Single Server Using PSO. *Procedia Materials Science*, 5, 2084-2089. https://doi.org/10.1016/j.mspro.2014.07.543

Noguera, J.H., & Watson, E.F. (2006). Response surface analysis of a multi-product batch processing facility using a simulation metamodel. *International Journal of Production Economics,* 102(2), 333-343. https://doi.org/10.1016/j.ijpe.2005.02.014

Ouzineb, M., Mhada, F.Z., Pellerin, R., & El Hallaoui, I. (2018). Optimal planning of buffer sizes and inspection station positions. *Production and Manufacturing Research*, 6(1), 90-112. https://doi.org/10.1080/21693277.2017.1422812

Patchong, A., & Kerbache, L. (2017). Transiting toward the factory of the future: Optimal buffer sizes and robot cell design in car body production. *IEEE International Conference on Industrial Engineering and Engineering Management* (1596-1601). https://doi.org/10.1109/IEEM.2017.8290162

Shaaban, S., & Romero-Silva, R. (2021). Performance of merging lines with uneven buffer capacity allocation: the effects of unreliability under different inventory-related costs. *Central European Journal of Operations Research,* 29(4). https://doi.org/10.1007/s10100-019-00670-9

Shao, H., Moroni, G., Li, A., & Xu, L. (2022). Heuristic Approach for a Combined Transfer Line Balancing and Buffer Allocation Problem Considering Uncertain Demand. *Applied Sciences*, 12(12), 1-37. https://doi.org/10.3390/app12126278

Smith, S., & Lasdon, L. (1992). Solving large sparse nonlinear programs using GRG. *ORSA Journal on Computing,* 4(1), 2-15. https://doi.org/10.1287/ijoc.4.1.2

Socconini, L. (2019). *Lean Manufacturing Paso a Paso*. Barcelona: Marge Books.

Tiacci, L. (2022). Buffer allocation vs. sequencing optimization: which of the two is most effective to improve the efficiency of assembly lines? *IFAC-PapersOnLine*, 55(10), 452-457. https://doi.org/10.1016/j.ifacol.2022.09.435

Wang, G., Song, S., Shin, Y.W., & Moon, D.H. (2014). A Simulation Based Study on Increasing Production Capacity in a Crankshaft Line Considering Limited Budget and Space. *Journal of Korean Institute of Industrial Engineers*, 40(5), 481-491. https://doi.org/10.7232/jkiie.2014.40.5.481

Weiss, S., Schwarz, J.A., & Stolletz, R. (2019). The buffer allocation problem in production lines: Formulations, solution methods, and instances. *IISE Transactions*, 51(5), 456-485. https://doi.org/10.1080/24725854.2018.1442031

Weiss, S., & Stolletz, R. (2015). Buffer allocation in stochastic flow lines via sample-based optimization with initial bounds. *OR Spectrum*, 37(4), 869-902. https://doi.org/10.1007/s00291-015-0393-z

Xi, S., Smith, J.M.G., Chen, Q., Mao, N., Zhang, H., & Yu, A. (2021). Simultaneous machine selection and buffer allocation in large unbalanced series-parallel production lines. *International Journal of Production Research*, 60(7), 2103-2125. https://doi.org/10.1080/00207543.2021.1884306

Zhou, B.H., Liu, Y.W., Yu, J.D., & Tao, D. (2018). Optimization of buffer allocation in unreliable production lines based on availability evaluation. *Optimal Control Applications and Methods*, 39(1), 204-219. https://doi.org/10.1002/oca.2341