

IMPROVING BUFFER STORAGE PERFORMANCE IN CERAMIC TILE INDUSTRY VIA SIMULATION

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ABSTRACT

This study aims at identifying the best strategy to temporarily store products within a buffer area in an Italian ceramic tile company. The storage policy is analyzed to maximize the storage capacity, facilitate operators' activities, and, consequently, improve the warehouse logistics performance. A discrete event simulation was conducted using Salabim, a Python based open-source software, in order to determine the best policy. We compare the performance of the current storage policy, based on technical production properties of products, and a newly proposed one, based on products' downstream destination. The results suggested that the proposed strategy significantly improves the performance of the buffer area management. The approach can be applied to different applications, contributing to the literature on simulation-based decision-making in material management. Furthermore, the study provides a functional case study showing the potential and achievable results of Salabim for modeling complex systems.

1 INTRODUCTION

Over the last decade, the worldwide tile market has experienced increasing significance and remarkable growth. In particular, as reported by ACIMAC Research Department (2022), the global production of tiles grew in general by 7.2% in 2021 compared to the previous year, producing 18.3 billion square meters. Focusing more on Italy, the country is the main world exporter in terms of value, accounting for 28.1% of the world export share, and ranking seventh in terms of production. Furthermore, Baraldi (2022) reveals that Italy produced 435 million square meters of tiles, generating revenues of €6.2 billion. Overall, in 2021, the Italian ceramic sector revealed a positive trend across all key indicators, highlighting its importance.

One of the crucial problems in ceramic industry operations is material handling. As defined in Efthymiou and Ponis (2019), material handling involves a range of activities to move, store, protect and control the products throughout the entire manufacturing process. In particular, products are briefly paused and handled

in storage areas, consuming valuable space and time in the form of person-hours and resulting in additional expenses for the company. Therefore, warehouse management, specifically material handling, plays a crucial role in ensuring efficiency and customer satisfaction within the supply chain.

Furthermore, Boza et al. (2014) introduced the concept of Lack of Homogeneity in the Product (LHP), a phenomenon that occurs during production processes when they involve uncertainty, such as natural raw materials or variable operations. The ceramic industry is particularly affected by LHP, due to clays and the highly variable production process, depending on various factors, such as temperature and humidity. The same authors pointed out that LHP is in contrast to customer demands, which in turn require uniform ceramic tiles for aesthetic reasons. To address this issue, tiles companies must incorporate a classification stage in their production process, involving personalized classification criteria. In particular, in most ceramic industries every piece is visually inspected and classified based on quality, shade, and caliber. Products are then stored in homogeneous subgroups to facilitate their retrieval for homogeneous orders. As a consequence, the classification process can affect material handling performance and, therefore, must be carefully evaluated. Hence, given the importance of material handling in ensuring material flow and avoiding bottlenecks, it is crucial to prevent production stops. Therefore, the objective of this study was to implement a Discrete Event Simulation (DES) in an Italian ceramic tile company, in order to analyze the best storage policy without affecting the material flow. Salabim (van der Ham 2018) was selected as simulation tool, as it offers a range of attractive features, including being an open-source Python-based software, having comprehensive documentation, object-oriented architecture, and animations. This work focused specifically on the comparison of two different storage policies for the classification of products within the buffer storage area. In particular, the newly devised policy classifies products based on their downstream destination rather than their production properties, consequently improving the logistic performance in terms of flexibility and costs.

The remainder of the paper is structured as follows. Section 2 provides an overview of the main research areas within the ceramic tile industry, with a particular focus on the applications of DES in the sector. In addition, a review of Salabim and its applications is provided. Section 3 presents more details about the problem, while Section 4 elaborates the proposed storage policy. Section 5 discusses in detail the simulation of the policy, and Section 6 reports and comments the results. Finally, Section 7 summarizes the study and presents future research directions.

2 LITERATURE REVIEW

The ceramic tile industry has received considerable attention in the literature, with many studies exploring different aspects of the industry. A large body of literature has investigated the production process of ceramic tiles. For example, Dubey and Yadava (2008) reviewed the Laser Beam Machine technology to improve the ceramic performance, while Sciancalepore et al. (2014) reviewed antibacterial and self-cleaning coatings for tiles. Moreover, Xie (2008) and Zhao (2021) examined innovative methods to identify tiles defects. More recently, the focus has shifted to the sustainability of the ceramic industry. Ferrari et al. (2019), Medina-Salgado et al. (2021), and Atılğan Türkmen et al. (2021) studied the estimation of the environmental impact of the ceramic industry. Focusing likewise on recycling, Andreola et al. (2016) and Zanelli et al. (2021) examined the usage of recycled materials in tile production, while Mangi et al. (2022) investigated the utilization of the ceramic waste for the production of concrete. Additionally, logistics aspects were studied from the sustainability perspective, as Dondi et al. (2021) highlighted the impact of the supply chain on the ceramic industry sustainability, focusing on identifying the potential criticality in the current consumption trends of raw materials. Moreover, Ma et al. (2022) pursued the achievement of a smart and sustainable manufacturing through the integration of big data analytics and digital twin technologies. The paper specifically focused on energy-intensive manufacturing companies and provided two different case studies on ceramic tile industries.

Furthermore, a growing body of literature has investigated Decision Support Systems (DSS) applications in various fields within the ceramic tile industry, such as the inventory control in Abdolazimi et al. (2021),

and the production planning and scheduling in Soares et al. (2022). In particular, Boza et al. (2014) and Alemany et al. (2018) specifically focused on the delivery management of products with homogeneity requirements, highlighting a crucial aspect of the ceramic tile sector.

Although considerable research has been done on different aspects of the ceramic industry, much less is known about the application of simulation in this sector. To the best of our knowledge, only a few papers investigated process simulation tools as performance measurement tools for improvement in ceramic tile industries. Davoli et al. (2010) developed a simulation tool to evaluate the impact of unreliable orders on the performance of a generic ceramic tile industry, quantified as earnings and fulfilled orders. The stochastic simulation divided the overall model into sub-processes, each simulated in VirtES, a customized simulation software coded in the Scilab environment. A precedent work of Davoli et al. (2008) studied the industrial processes of ceramic tiles manufacturing through the integration of VirtES and AutoMode. Firstly, each industrial process was schematized in terms of input and output and simulated in VirtES, to investigate critical processes and support the process redesign. Then, the impact of the proposed changes was quantified in terms of production, using the AutoMode commercial process-oriented simulation tool. Similarly, Nadir et al. (2020) studied the waste generated by non-efficient tile handling systems, simulating the process in commercial Simio software and comparing the results with performance indicators. However, to the best of our knowledge, no studies have simulated ceramic processes using non-commercial software tools. Therefore, we filled the literature gap by studying the storage policy of a ceramic company through the application of simulation, in particular DES on Salabim, an open-source package developed in Python.

Salabim was presented by van der Ham (2018), who focused on the characteristics that differentiate Salabim from SimPy, the other open-source simulation software developed in Python. Firstly, Salabim uses the Simula activate/passivate/hold paradigm, which facilitates the implementation of clear and easy-to-maintain models. The Simula approach, introduced by Dahl and Nygaard (1966), enables the modeling of interactions among simulation entities by defining events and changes of state. Moreover, Salabim provides various additional and useful functions such as animation, queues, states, monitors for data collection and presentation, tracing, and statistical distributions.

However, despite its promising characteristics, we were able to find little literature about Salabim. In Lang et al. (2021b), a problem case was used to compare five different DES software tools. In particular, the authors considered three open software tools, including Salabim, and two commercial ones. The results proved that open-source simulation software is a concrete alternative to commercial DES software. Although not first in the ranking, Salabim emerged as a promising tool for DES, particularly recommended to integrate models in Python applications. Several attempts have been made to integrate Machine Learning and DES in Salabim to solve different problems. The main area of interest within the Salabim applications is the simulation of variants of the production scheduling problem, as in Erden et al. (2019, 2021) and Lang et al. (2020a, 2020b, 2021a, 2021c). Furthermore, in Anglano et al. (2019a), and Anglano et al. (2019b), the authors focused on algorithms for the scheduling of applications on a set of heterogeneous mobile devices. Finally, Salabim was also used to simulate operations in health centers, as in Baldwa et al. (2020) and Shoaib and Ramamohan (2022).

Considering the literature gap, this paper aims to provide a concrete application of DES in the logistics of the ceramic tiles industry. Thus, in the following chapters, we will focus on the Salabim application to the case study.

3 PROBLEM DESCRIPTION

This research concerns a international ceramic company that produces tiles according to the make-to-stock strategy. The study first simulates the policy adopted to classify products in the buffer storage area between the production plant and the logistics department. The storage policy is then redesigned as a strategy to maximize the storage capacity, facilitate operators' activities, and, consequently, improve the warehouse logistics performance.

Buffer areas in the ceramic sector are commonly standardized and regularly shaped and therefore they can be schematized as a matrix, as shown in Figure 1. Each cell of the matrix can contain a pile of four identical-sized pallets, vertically stacked. The pallets are transported by automatic vehicles into the storage area from the east side (in the bottom of Figure 1) and are temporarily stored in the buffer, waiting for the forklift operators on the west side to manually pick them up and finally pack them into the logistics department. Since operators pick pallets manually from the buffer area, their work efficiency is impacted by the location of the pallets. Consequently, the storage policy must carefully assign pallets to cells, dividing pallets into classes based on criteria to cluster them and facilitate picking activities.

To facilitate workers activities, each column of the matrix is dedicated to a single class. Specifically, pallets are deposited into the westernmost available cell of a column dedicated to their class. In case all columns have already been destined to other classes, the system can store distinct classes in the same column, to prevent production downtime. However, mixing classes causes penalties because it hampers operators' activities. Classification policies are described in detail in Section 4.

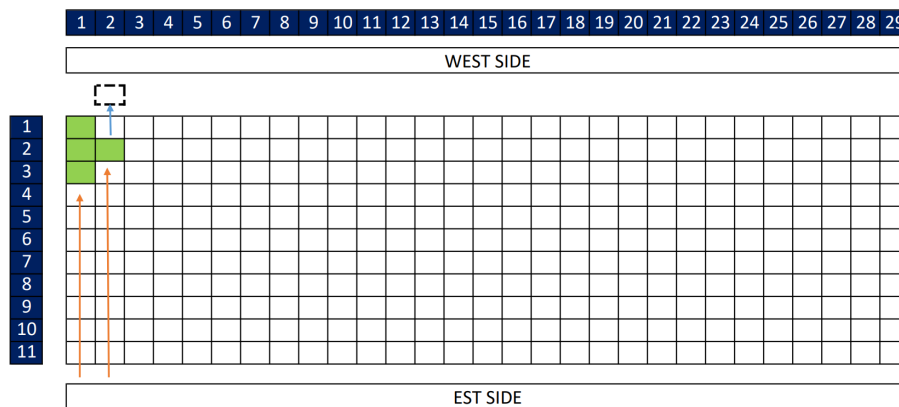


Figure 1: Storage area representation.

4 CLASSIFICATION POLICIES

4.1 Current Classification Based on Codes

The current strategy classifies columns based on codes, identified by the combination of:

- commercial characteristics, such as size, materials, lapping, and thickness;
- technical specifications, such as quality, shade, caliber, and production batch.

Each column can hold only one single code. In case all columns have already been destined to different codes, the system can store distinct codes in the same column, causing penalties.

4.2 Proposed Classification Based on Destinations

This study focuses on the definition of a proposed storage policy, categorizing pallets according to their final destinations rather than their codes. Pallets with different downstream destinations, established by in-house logistics flows, are moved to dedicated company warehouses. Therefore, each destination may require pallets to be classified based on further characteristics. The following list outlines the range of possible destinations and indicates the corresponding classes for each one:

- *inter-company pallets*, containing tiles produced for other companies of the same holding. In this case, pallets are classified based on the commercial characteristics of the products;

- *under-choice pallets*, containing non-first quality tiles due to LHP. Such pallets are commercialized in a different commercial channel and, therefore, are shipped to a specific facility. In this case, pallets are not classified based on further characteristics;
- *picking pallets*, destined for picking operations, in which loading units containing fewer tiles than regular-size pallets are prepared to meet sales requirements. In this case, pallets are not classified based on further characteristics;
- *high-rotation pallets*, containing frequently sold goods. They are stored in a warehouse closer to the shipping area. In this case, pallets are sold, and consequently classified, based on their code, that comprehend both technical and commercial characteristics;
- *low-rotation pallets*, containing goods that are sold less frequently. They are stored in a warehouse farther from the shipping area. Also in this case, pallets are sold, and consequently classified, on the basis of their code.

Each column of the buffer area is dedicated to a single class. As in the current storage policy, if all columns have already been destined to other classes, the new policy allows mixing pallets to avoid any stop in the production flow. In this case, whenever a new pallet has to be stored in an already classified column, there are two possible scenarios:

- *soft-mix*: the pallet is stored inside a column dedicated to the same destination, but to a different class. For example, a *soft-mix* class column can contain different codes of inter-company pallets;
- *mix*: the pallet is stored inside a column dedicated to a totally different destination. For example, a *mix* class column can contain both under-choice and picking pallets.

The new classification storage policy was rigorously analyzed through a DES to quantify its impact on major performance indicators.

5 SIMULATION

In this section, we provide a description of the simulation study, including the input data provided to model the process, the conceptual model used to reproduce the real-world system, the verification and validation processes, and the performance indicators selected to measure the effectiveness of the proposed solution.

5.1 Input Data

The simulation is based on real world data that reproduces the manufacturing jobs of 30 different days in the company. Therefore, the initiation of the simulation requires an input file for each simulated day, containing real information on each pallet that arrived in the buffer area. The relevant data contained for each pallet includes the identification number and the size of the pallet, its arrival time inside the buffer area, the production characteristics of the tiles, and the information about its downstream destination, such as the level of rotation and whether the pallet is inter-company, under-choice or picking. To generate the necessary input data about downstream destination, a pre-processing step was executed on historical data, calculating the information using company sales data. Since LHP particularly affect the quality of the ceramic tiles, special attention was dedicated to under-choice pallets, consider their stochastic fluctuations. To gain insights into the variability of under-choice pallet, a histogram was initially plotted to visualize the distribution of the number of pallets. Subsequently, the Shapiro-Wilk statistical test was performed, confirming that the number of daily under-choice pallets follows a normal distribution ($mean = 28.89, std = 8.26$). As a result, we used this distribution to stochastically generate data and we performed 10 simulation runs per day.

5.2 Conceptual Model

The simulation aims to improve the utilization of the buffer area by determining the best storage classification policy. The flow of the simulation is schematized in Figure 2. At first, the simulation is initialized with

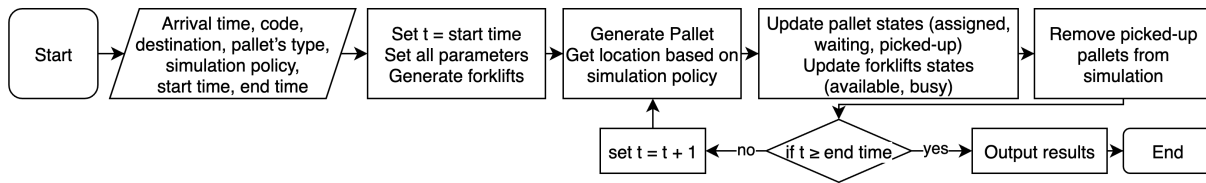


Figure 2: Simulation flow.

the necessary input parameters. Each pallet undergoes four key phases:

- *Creation and Classification*: after being generated, the pallet is classified according to either the characteristics-based or the destination-based policies;
- *Storage*: the pallet’s storage location in the buffer area is determined based on space availability, with the westernmost position being favored. If no space is available, the pallet is removed from the simulation and considered lost, according to the real-world process, in which if there is no space available then the production line must stop. AGVs transport pallets to the storage area, following the triangular distribution obtained from real-world data ($min = 90, max = 180, mode = 120$);
- *Queuing*: the pallet waits at the storage location;
- *Pick-Up*: the pallet is removed from the buffer area by forklift operators and exits the simulation. Two forklift operators are responsible for the emptying process during working hours and they are considered available when there are not pallets waiting to be removed.

The simulation model was developed by extending Salabim’s built-in classes and regulating its flow through the construction of built-in component routines. The main simulation components extended from Salabim’s built-in classes are *PalletClass*, *PalletGeneratorClass*, and *ForkliftClass*. *Operators*, *BufferArea*, *ColumnState*, and *Animation* are entities created respectively from Salabim’s built-in classes Resources, Queue, State, and Animate.

Figure 3 illustrates the logic of the conceptual model through the pseudocode. The *PalletGeneratorClass* generates pallets according to the input data (Line 3), ensuring that the creation of pallets within the simulation corresponds to the actual arrival times specified by the input data. After the generation of each pallet, the associated routine of *PalletClass* (Line 14) is automatically executed. The routine determines the pallet’s location within the buffer area, the placement of the pallet in the appropriate queue, the activation of the

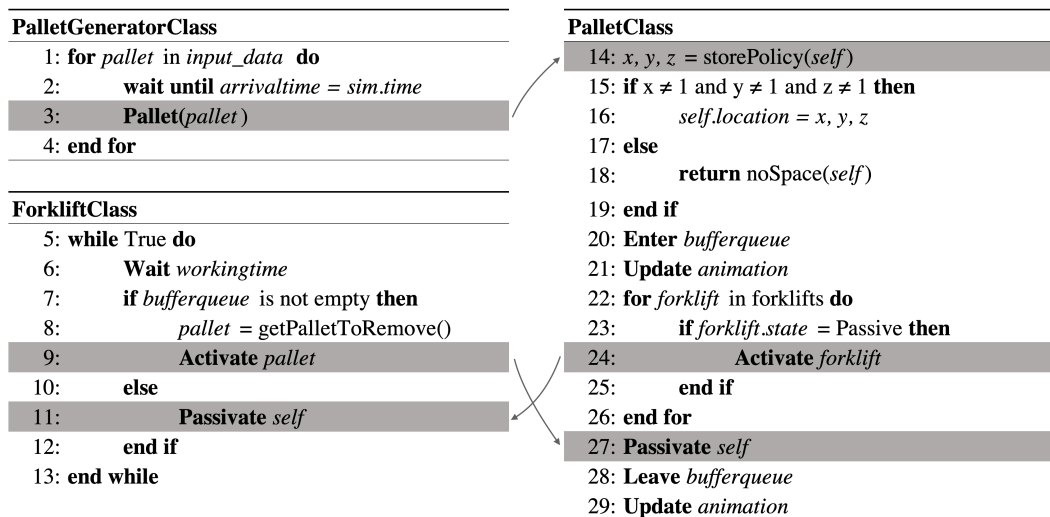


Figure 3: Conceptual model’s pseudocode.

ForkliftClass if it is in a passive state (Line 24), and finally the passivation of the pallet (Line 27). The *ForkliftClass* models the activities of the operators by removing pallets from the buffer area during working hours, emptying one column at a time. When the pallet is reactivated by *ForkliftClass* (Line 9), it exits the buffer area queue, updating the 2D animation representation.

5.3 Verification and Validation

The conceptual model was verified to confirm its accuracy. To ensure verification, the documentation was kept up-to-date throughout the model construction process and the accuracy of the model was evaluated by analyzing the output while modifying the input parameters. Moreover, Salabim’s 2D animation was used to visually inspect the model’s logic. Figure 4 represents an example of the animation, in which different colors are used to represent distinct classes, in order to highlight any presence of mixed columns. For each cell we also report the number of stacked pallets.

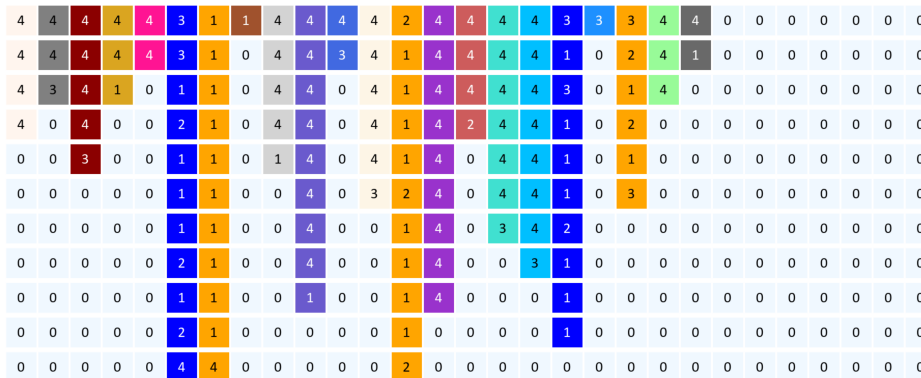


Figure 4: Simulation 2D animation.

Finally, validation was achieved by comparing the average waiting time of pallets in the buffer area for simulation results and actual data regarding 30 different days. Since waiting times were normally distributed, the paired *t*-test was selected to compare results and determine a statistical difference. The test did not show any significant difference in the average time of the 30-day data (*p*-value > 0.9) and, as a result, the simulation is considered accurate and a valid representation of the real-world process.

5.4 Performance Indicators

The purpose of the simulation was to assess possible improvements in the buffer area in terms of space utilization and ease of operation. The simulation assessed the performance of a company in which the production process never stops, while the logistics department operates on a two-shift schedule, as common in the ceramic sector. As a result, during night shifts and weekends, pallets are stored in the buffer area without being retrieved. Therefore, two distinct sets of indicators were collected to evaluate both the described scenarios – with and without operators. In the scenario without operators, the following performance indicators were assessed to evaluate the impact of the classification policies:

- time (in minutes) elapsed before the first occurrence of the *mix* state in the current policy and the *soft-mix* state in the proposed one;
- time (in minutes) elapsed before the area being filled;
- number of pallets lost due to lack of space.

The real-world system was designed to enable operators to handle the production flow without exceeding the available buffer storage area. Therefore, in the scenario with operators, the focused moved from

the probability of the area being filled to the assessment of space utilization, considering the following performance indicator:

- maximum number of columns used at the same time, calculated to assess the feasibility of the classification policy in terms of space utilization.

The performance indicators were collected considering the two classification policies presented in Section 4 and the results are compared in Section 6.

6 EXPERIMENTAL RESULTS

Two scenarios were simulated to compare the current classification policy and the proposed one based on the performance indicators defined in Section 5.4. The mean results of 10 runs for each one of the 30 simulated working day are presented in Table 1. Given that each simulation day begins at the end of the logistics shift and considering that the real-world system was designed to ensure operators empty the area before the shift ends, the buffer area starts the simulation without any pallets, making warm-up time unnecessary. A statistical comparative analysis was performed on the results to determine a significance difference between

Table 1: Simulation results.

Day	Without operators						With operators	
	Minutes before mix/soft-mix state		Minutes before area filled		Number of lost pallets		Max. number of columns	
	Current	Proposed	Current	Proposed	Current	Proposed	Current	Proposed
1	634.2	774.1	1322.8	1334.7	57.7	55.1	26.0	23.5
2	660.7	779.6	1297.2	1469.6	45.9	0.0	28.5	24.2
3	388.3	486.0	1229.0	1177.8	80.4	108.0	29.0	29.0
4	511.4	695.3	1174.4	1230.9	113.2	68.9	28.3	25.1
5	790.9	1019.2	1391.7	1432.2	43.6	3.2	22.2	16.2
6	453.0	681.7	1280.3	1319.1	83.6	53.9	28.8	25.9
7	776.1	966.9	1421.7	1495.9	0.0	0.0	21.3	17.1
8	527.0	729.4	1395.9	1367.5	14.3	20.7	26.9	23.7
9	602.3	851.0	1382.6	1409.9	32.9	15.8	26.3	22.0
10	881.9	948.7	1474.1	1429.8	0.8	2.5	22.3	18.6
11	600.2	718.9	1311.6	1364.3	49.6	31.5	26.8	23.4
12	759.0	847.9	1467.7	1467.6	0.0	0.0	23.6	20.7
13	715.1	972.9	1305.4	1378.5	49.8	22.6	23.7	19.1
14	618.1	887.4	1309.7	1451.8	61.6	1.5	26.8	21.8
15	764.1	803.0	1370.1	1402.7	16.0	4.8	26.2	21.7
16	481.8	694.8	1356.2	1424.7	55.8	14.7	28.8	24.6
17	747.1	930.6	1361.7	1442.0	34.0	1.0	24.7	21.1
18	601.3	782.8	1327.7	1256.4	0.0	0.0	18.8	17.3
19	530.5	913.7	1262.4	1435.5	85.5	2.7	28.3	23.1
20	1004.8	1099.0	1524.0	1498.4	0.0	2.5	22.2	18.7
21	539.5	724.8	1203.5	1245.6	79.5	70.7	28.1	22.9
22	580.0	758.4	1454.7	1419.5	2.7	4.0	26.2	22.4
23	430.6	534.5	1109.4	1118.6	195.5	203.8	29.0	28.6
24	699.6	910.9	1367.9	1476.5	22.6	1.0	25.6	22.1
25	620.1	836.1	1361.3	1477.7	17.7	0.0	26.4	23.6
26	780.6	1178.9	1488.3	1595.0	3.2	0.0	23.1	19.8
27	646.8	835.1	1368.1	1392.4	43.0	37.5	25.6	20.9
28	734.3	937.4	1525.7	1408.2	0.0	9.5	22.2	18.1
29	878.3	928.0	1436.8	1399.6	3.4	35.5	23.2	20.6
30	385.1	511.5	1157.3	1169.2	150.6	157.9	29.0	28.2

the means of the two simulated policies. For normally distributed results, the one tail paired t -test was selected, while non-normally distributed data were compared through Wilcoxon signed-rank test.

Regarding shifts without operators, the test revealed that the mean time elapsed before the first occurrence of the *mix* state in the current classification policy and the *soft-mix* state in the devised policy significantly differ (p -value $< 10^{-12}$). On average, the *soft-mix* state in the new policy occurs 27.9% minutes later than the *mix* state in the current policy, significantly reducing the operation time. Furthermore, the test was conducted on the mean time elapsed before the area was filled. The test demonstrated a significant difference (p -value $< 10^{-2}$), with the new policy delaying the area filling time by 2.6% compared to the current one, leading to capacity improvements and consequent reductions in production downtime. Additionally, statistical analysis revealed a significant reduction in the mean number of lost pallets (p -value $< 10^{-2}$), with an average decrease of 30.8%. The discussed results showed how the proposed policy enhances the flexibility of the storage activities in the scenario without operators. Therefore, the company can reconsider the number of required operators and the distribution of the shifts, resulting in economic benefits. In shifts with operators (reported in the right part of Table 1) the test demonstrated a significant difference in the mean number of columns required (p -value $< 10^{-13}$), highlighting the possibility to compress the size of the buffer area about the 13.5% without reducing the production capacity. Overall, the experimental results confirmed the benefits of the devised policy, both in terms of economic efficiency and flexibility. Further economical studies were conducted to estimate the potential cost savings associated to the area emptying process, revealing that the proposed policy is expected to reduce the costs by 17%.

The results outlined how the developed policy led to a statistically significant improvement in the performance of the buffer storage area. However, it was essential for the company to comprehend how the new policy would impact different scenarios. This understanding became particularly relevant due to the positive market trends observed in the ceramic sector and particularly within the company. Therefore, the assumption of a percentage increase in production was made to assess the potential impact of the policy under varying conditions. Specifically, seven different scenarios were simulated, incrementally increasing production quantity by 5%, from 0% to 30%. For each scenario, the simulation was conducted over a period of 30 days, and the mean results of 10 runs per scenario are reported in Table 2. To assess the efficiency of the proposed policy, statistical tests were conducted, which revealed that the devised policy outperformed the current policy in all seven scenarios, regardless of the production increase. Figure 5 presents four graphs, each one displaying the mean simulation results for a distinct performance indicator. The first graph shows a significant increase in the time elapsed before the occurrence of the *mix/soft-mix* state with the proposed policy for all production quantities, resulting in a steady improvement in performance of approximately 27.2% for each scenario. Furthermore, the second graph demonstrates that the time before the area is filled improves for all production levels, saving approximately 2.4% of the time. The third graph shows that the number of lost pallets decreases with the new policy, although the percentage improvement decreases with an increase in production, due to an increase in the absolute number of lost pallets. Moreover, the number

Table 2: Average simulation results for increasing percentages of production quantity.

Increase in production (%)	Without operators						With operators	
	Minutes before mix/soft-mix state		Minutes before area filled		Number of lost pallets		Max. number of columns	
	Current	Proposed	Current	Proposed	Current	Proposed	Current	Proposed
0	644.8	824.6	1348.0	1383.1	44.8	31.0	25.6	22.1
5	599.0	767.2	1269.8	1295.8	77.0	62.6	26.6	23.7
10	580.4	735.5	1203.2	1232.3	112.9	98.7	27.3	24.7
15	552.8	701.9	1148.2	1176.9	151.7	137.3	28.3	25.9
20	532.8	672.9	1098.7	1123.9	190.9	177.5	28.4	26.7
25	506.3	643.7	1050.9	1078.6	232.7	216.7	28.6	27.4
30	487.1	617.3	1012.2	1038.6	269.7	256.9	28.8	27.8

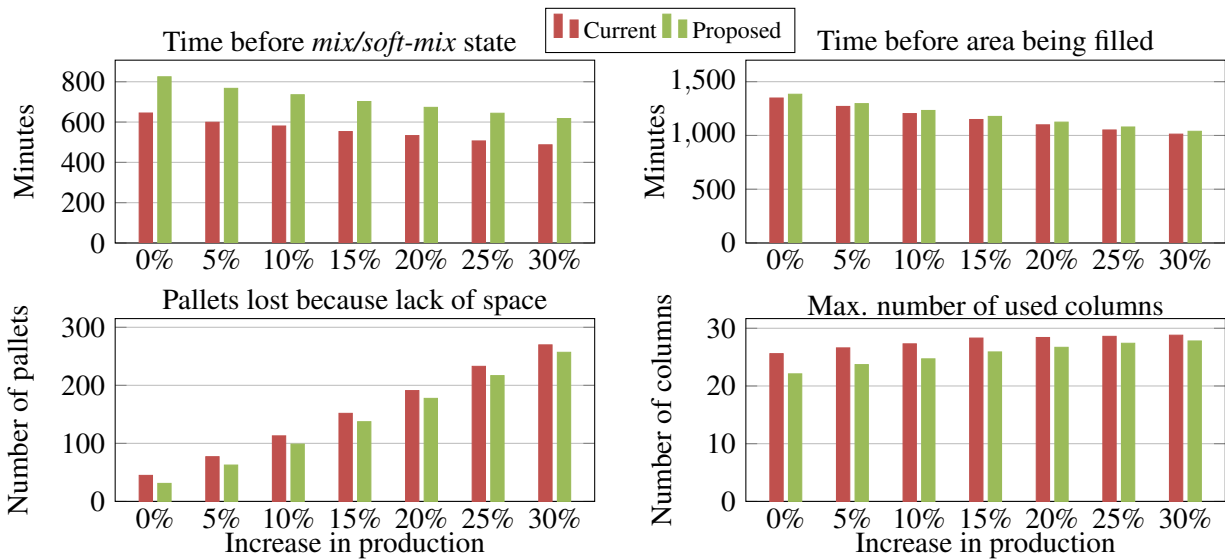


Figure 5: Mean simulation results for increasing percentages of production quantity.

of storage columns used during operator shifts is shown in the fourth graph and it decreases by an average of 7.9%, allowing for the possibility to reduce the buffer area size. Overall, the proposed policy demonstrates its effectiveness in all scenarios, highlighting its potential to improve performance and enhance economic and flexibility improvements.

7 CONCLUSION

The study aimed at determining the best strategy to temporarily store products within a buffer area in an Italian ceramic tile company, in a highly uncertain context characterized by LHP. The identification of an effective policy is crucial for ensuring streamlined material flow and reducing operational costs. In particular, in a highly variable production scenario, where homogeneous batches are essential to meet customer demand, an effective storage policy must classify products into homogeneous subgroups. The policy proposed by this study focused on the subdivision of products in the buffer area according to their downstream destination, rather than their technical production characteristics, as it is currently done by the company. The approach aimed at improving the buffer area management, increasing available space and reducing the intermixing of products belonging to different sub-categories. To compare the effectiveness of the current and proposed policies, a discrete event simulation was conducted using Salabim. The model was rigorously verified and validated, and simulation results were obtained for both policies and compared.

The results indicated a statistical difference between the two policies. In particular, it was demonstrated that the new policy improved the column classification of the buffer area, consequently reducing the number of required columns. This provided the company with the opportunity to either reduce the buffer area's space or increase production capacity. Also, the proposed policy delayed the filling of the area, preventing production stoppages that could negatively and significantly impact the company's profits. In addition, the new policy reduced the number of times in which non-homogeneous subgroups were in the same column, consequently accelerating operators' tasks. Furthermore, besides the measured results, pallet subdivisions based on downstream classification could further reduce the time required for subsequent operations. Therefore, the company could profit from both economic and flexibility advantages, providing strategic benefits to managerial decision-makers. Moreover, the sensitivity analysis showed that the new policy benefits the performance even in the scenario of increased production quantity. For these reasons, the company decided to change their storage policy according to the results of the study, classifying their products in the buffer area based on downstream destination.

Finally, the simulation model developed in this study is a valid representation of the process and can be utilized for further research regarding new classification policies for continuous improvement.

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