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AN ALGORITHM FOR SIMULATION AND STOCHASTIC SPATIAL OPTIMIZATION OF THE SAUSAGE PRE-SMOKING HOLDING PROCESS

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Abstract: The objective of this study was to create a simulation-based model to optimize the logistics of industrial sausage pre-smoking holding. Due to the high computational complexity and the high number of coupled degrees of freedom, a modification of the Monte Carlo method was implemented. The simulation results demonstrated and quantified the influence of key spatial and temporal parameters describing the sausage pre-smoking holding process. The stochastic optimization algorithm provided a total delay reduction of 25–40% and an end delay reduction of up to 76% for different arbitrarily conceived, although varied, high-volume production plans. The results indicated that pre-smoking holding delays in lower-volume production could be difficult to minimize.

Keywords: production logistics, stochastic optimization, Monte Carlo method, simulation model, pre-smoking holding, meat processing.

1. INTRODUCTION

Pre-smoking holding is a passive process in sausage manufacture whose purpose is to even out the ingredient and flavor distribution inside the casing [Bykowski & Wilczyńska, 2010] while also acting as a preliminary stage of drying. It succeeds stuffing and precedes thermal processing, chiefly smoking [Migdał et al., 2023]. The pre-smoking holding temperature is usually close to 20°C (68°F), which is usually achieved in the vicinity of the thermal processing infrastructure. Lower temperatures lead to a decrease in the kinetic reaction speed and a sharp increase in the pre-smoking holding time [Korzeniowska-Ginter & Keller, 2019; Adeyemi & Abdulkadir, 2025].

Pre-smoking holding causes water to migrate toward the surface, increasing water activity and the potential for chemical and biological reactions [Arnau Arboix, 2025]. Semi-finished meat products absorb harmful substances, most notably polycyclic aromatic hydrocarbons (PAHs), such as benzo[a]pyrene [Nizio et al., 2023]. Unrested meat products have been found to be much more susceptible to the absorption of PAHs

during smoking as opposed to rested products [Migdał et al., 2017]. On the other hand, an excessively long holding time may lead to an accumulation of physical and chemical contamination. Vegetative microorganisms present in the air may also be absorbed by the muscle [Redondo-Solano et al., 2016]. For the reasons listed above, it is crucial to maintain the holding time to minimize product quality losses.

The pre-smoking holding process starts immediately after the sausage is formed inside its casing. It is then hung on metal rods and placed on the rack of a specialized smoking trolley, on which it should then be transported to a designated pre-smoking holding spot for a specified time [Wawrzyniak et al., 2023]. This holding time depends on the diameter and composition of the stuffing. It takes around thirty minutes to an hour for homogenized sausages, and up to 2–3 hours for other products [Latoch, 2024]. Some products, such as the traditional Polish kabanos sausage, may require over 14 hours of holding time. Additional procedures, such as weighing, reporting and scraping of stuffing residue, may be exercised before the trolley is placed in the area in question. After the product was finished holding, it should be transported to the thermal processing segment, consisting primarily of smoking chambers.

Another aspect of any production process is employee labor and, in the case of automated production, energy and maintenance. Transportation tasks account for 56% of the activities in the meat industry [Kabiesz & Bartnicka, 2018]. Delays caused by the pre-smoking holding process may lead to unplanned overtime, increasing salary and energy costs. They may also contribute to delays in the following unit processes and ultimately shipping delays, or reduced availability of the product. More complex production plans have been found to be more prone to delays [Kiriş & Ünal, 2020]. It is therefore important to minimize the time between the production of the last batch and its placement in the smoking chamber. An increase in demand requires proper scaling of the production plans, which includes development of the infrastructure and preferably automation [Samúelsson, 2019]. Queue planning in sausage production benefits greatly from queuing theory-based optimization models [Banjarnahor, 2024].

Sausage pre-smoking holding itself is a passive process and it should not be parametrized. However, the delays depend not only on the mean operator speed, but also on the distance the operators need to cover with the products and back. That distance, on the other hand, depends on the placement of the trolleys containing the products to be held. It is therefore crucial to actively minimize the path between the trolleys and the thermal processing area, while ensuring that newly placed trolleys do not obstruct those with the product closer to finishing the holding process.

A knowledge of the parameters contributing to the delays in the pre-smoking holding process and the accompanying degrees of freedom allows the formulation of an optimization problem. Since material and information flow organization is crucial for reducing losses in the food industry, an important step in production planning is conceiving an accurate and reliable predictive model describing the processes being considered [Gailan Qasem et al., 2021; Therdthai, 2021]. Most of these processes, including pre-smoking holding, thermal processing and routing for different food

products, are computationally difficult and require evolutionary algorithms to optimize [Lemma et al., 2014; Roy et al., 2020]. Due to the high computational complexity, logistic problems for the perishable food production industry often use stochastic approaches [Pratap et al., 2022].

A random search with memory is the simplest example of a metaheuristic algorithm [Lones, 2011; Tsai & Chiang, 2023]. Several researchers have created random search-based algorithms for food production and supply optimization [Wari & Zhu 2016]. Examples of computationally hard problems solved with random search algorithms that can be found in the literature include tracking optimal retort temperature for canned foods and vehicle routing optimization [Simpson et al., 2008; Abakarov et al., 2009; Pacheco et al., 2012]. Different metaheuristic approaches can also be found for food industry logistic problems, such as genetic or agent-based algorithms [Akpınar, 2021; Katiyar et al., 2021]. However, no logistics models or optimization algorithms directly dedicated to sausage pre-smoking holding can be found in the literature.

The aim of this study was to create an algorithm to minimize quality losses stemming from resting delays, using a simplified model describing the logistics of intra-facility smoking trolley transport. Such a model should consider the pre-smoking holding process, which causes many trolleys to be placed in a confined space for a preferably unchanging time. It was parametrized with the most important spatial and temporal parameters, which could be determined for any meat processing plant. A stochastic optimization algorithm utilizing the model created was also developed and assessed.

2. METHODS

The deterministic logistic model describes the actions taken by the production employees from both sides of the pre-smoking holding space and the methods of their evaluations. For the sake of simplicity, the pre-smoking holding area **A** was expressed in matrix form, of dimensions W and L , normalized to the square base trolley dimension (td). Optimization methods used in the production industry make use of statistical models [Fernandes et al., 2020]. Table 1 lists all spatial parameters defined for the pre-smoking holding process.

Table 1. Spatial parameters of the sausage pre-smoking holding process

Parameter	Symbol	Unit	Assumed impact
Area width	W	td	negative
Area length	L	td	negative
Mean pushing/pulling speed	v_t	td/s	positive

Table 1, cont.

Mean untooled (non-pushing, non-pulling) operator speed	v	td/s	positive
Number of smoking chambers	C	–	positive
Distance between smoking chambers	l_c	td	negative

Source: own study.

2.1. LOGISTIC MODEL AND PROBLEM FORMULATION

For the sake of simplicity, the distance s between the two points $[x = x_0; y = y_0]$ and $[x = x_a; y = y_a]$ is approximated as a Euclidean distance, according to Equation 1.

$$s = \sqrt{(x_a - x_0)^2 + (y_a - y_0)^2} \quad (1)$$

The pre-smoking holding process involves two operators (or teams of operators) on the opposite sides of the holding area, with equal v_t and v . The first operator (or team of operators) is responsible for relocating the trolleys from the waiting point $[x = 1; y = 0]$ to the designated spots and returning to the waiting point. The time t_1 required for this move can be calculated from Equation 2.

$$t_1 = s \left(\frac{1}{v_t} + \frac{1}{v} \right) \quad (2)$$

The second operator (or team of operators) is responsible for placing the trolleys inside one of the C smoking chambers once the product is finished holding. Their waiting point is located at $[x = W; y = L + 1]$. The time t_2 taken can be calculated from Equation 3.

$$t_2 = (s + C \cdot l_c) \left(\frac{1}{v_t} + \frac{1}{v} \right) \quad (3)$$

The sausages should be made in regular intervals of time, placed for a set amount of time and then taken to the smoking infrastructure. Additional dispatch procedures, such as weighing, may occur before the product is transported. Table 2 lists the temporal parameters relevant to the process under consideration.

When product i is made within T_{pi} minutes, it should be dispatched within T_{di} minutes by the first team, then placed in a dynamically designated spot. After not less than T_{ri} minutes it should be placed in a smoking chamber for T_{si} minutes, after which the chamber is freed automatically. No new products are made after T minutes elapse.

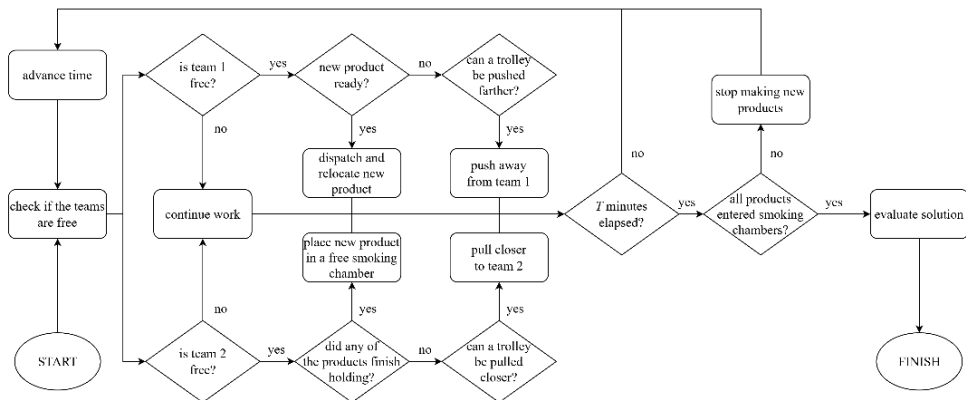
Table 2. Temporal parameters of the sausage pre-smoking holding process

Parameter	Symbol	Unit	Assumed impact
Production time of product i	T_{pi}	min.	positive
Dispatch time of product i	T_{di}	min.	negative
Pre-smoking holding time of product i	T_{ri}	min.	positive
Smoking time of product i	T_{si}	min.	negative
Total process timeframe	T	min.	neutral

Source: own study.

Figure 1 presents the flowchart describing the logistics regarding the processes of pre-smoking holding and smoking. The new trolleys should be placed by the first operator (team) as close to the smoking infrastructure [$x = W$; $y = L$], and as far away from [$x = 0$; $y = 0$] as possible, if the spot is not obstructed. The second operator (team) should prioritize the products which finished holding the earliest, again if they are not obstructed.

If either of the two operators (teams) is idle, they should work on bringing the trolleys closer to the smoking area (maximize y). The time taken to relocate the trolley can be calculated using Equation 2.

**Figure 1.** Pre-smoking holding logistics algorithm flowchart

Source: own study.

The main objective of the sausage pre-smoking holding optimization task is to find the vectors of the timestamps, product indices and coordinates of the

consecutively placed trolleys $\mathbf{T}, \mathbf{P}, \mathbf{X}, \mathbf{Y}$, consecutively removed trolleys $\mathbf{T}', \mathbf{P}', \mathbf{X}', \mathbf{Y}'$, as well as the smoking chamber indices $\mathbf{C}$, that minimize the total pre-smoking holding delays, denoted as τ . They can be defined as the sum of all n unit delays τ_i , as described in Equation 4. The unit delays result from more products being made at once and waiting for dispatch or, more importantly, holding for a longer time than needed.

$$\tau(\mathbf{T}, \mathbf{P}, \mathbf{X}, \mathbf{Y}, \mathbf{T}', \mathbf{P}', \mathbf{X}', \mathbf{Y}', \mathbf{C}) = \sum_{i=1}^n \tau_i(t_i, p_i, x_i, y_i, t'_i, p'_i, x'_i, y'_i, c_i) \rightarrow \min \quad (4)$$

Another objective function definable for the sausage pre-smoking holding optimization task is the end delay τ_{end} , describing the overtime resulting from the last few products not being fully processed at the end of the production timeframe T . It can be defined according to Equation 5, as the difference between T and the time elapsed between the beginning of the production timeframe and placement of the last product in a smoking chamber, denoted as T_{el} . Since the last product made may not be finished holding at $T_{el} = T$, a certain delay is unavoidable.

$$\tau_{end}(\mathbf{T}, \mathbf{P}, \mathbf{X}, \mathbf{Y}, \mathbf{T}', \mathbf{P}', \mathbf{X}', \mathbf{Y}', \mathbf{C}) = T_{el}(\mathbf{T}, \mathbf{P}, \mathbf{X}, \mathbf{Y}, \mathbf{T}', \mathbf{P}', \mathbf{X}', \mathbf{Y}', \mathbf{C}) - T \rightarrow \min \quad (5)$$

Depending on the volume of production, the number of possible placements could be close to $(CWL)^{2n}$, where n is the total number of trolleys of manufactured products. The matrix representation of the pre-smoking holding area can also be interpreted as a fragment of a square lattice, consisting of all pre-smoking holding area $\mathbf{A}$ lattice points and the operator waiting locations $[x = 1; y = 0]$ and $[x = W; y = L + 1]$. Most lattice problems are NP-hard [Aggarwal et al., 2022].

2.2. OPTIMIZATION PROCEDURE

To search for the optimum solution to the NP-hard sausage pre-smoking holding problem, a modified version of the Monte Carlo method was used. Stochastic methods are often used in computationally complex spatial optimization problems [Kuo et al., 2020]. The Monte Carlo method, conceived by Ulam, Metropolis and Neumann in 1950, is widely used in problems which are difficult or impossible to solve analytically, including optimization, numerical integration and statistics [Kroese et al., 2014]. It has found its application in the meat processing industry as well [Koroteev et al., 2022]. This method assumes creating a random and mutually independent solution for every one of N epochs and recording it if it proves to be better than the solution currently stored in memory [Lisowski, 2017]. This course of action can be described with the flowchart presented in Figure 2. In this modification, the best-found configuration that minimizes the objective function (τ or τ_{end}), as well as its value, is saved in memory to be compared against in its subsequent evaluations. The algorithms used for obtaining the initial and random solutions are described with the flowcharts presented in Figure 3.

The method of obtaining the initial deterministic solution is shown in Figure 3a, whereas the method of obtaining the random solutions is shown in Figure 3b.

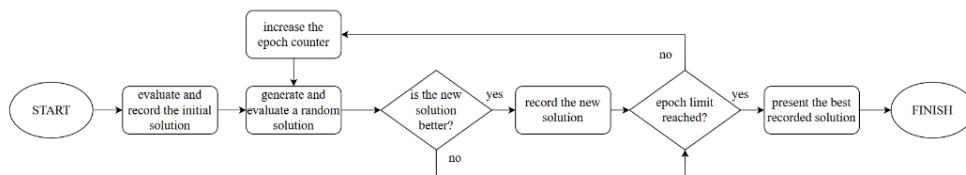


Figure 2. Monte Carlo algorithm flowchart

Source: [Lisowski, 2017].

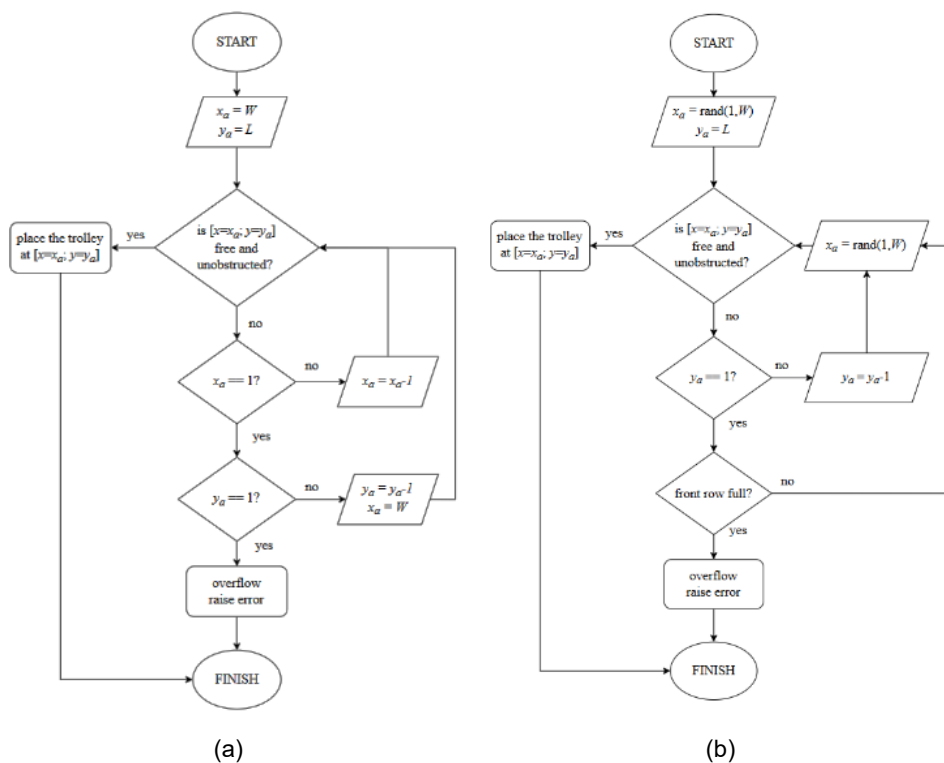


Figure 3. Flowcharts of the algorithms for obtaining the initial solution (a) and stochastic solutions (b)

Source: own study.

2.3. COMPUTATIONAL EXPERIMENTS AND EVALUATION CRITERIA

To measure the optimization performance in relation to the initial solution, a relative improvement (*RI*) unit was defined. It denoted the percentage of delays avoided while applying the best-found configuration. *RI* for the best found τ^* relative to τ_0 from the deterministic solution can be calculated using Equation 6.

$$RI(\tau) = \left(1 - \frac{\tau^*}{\tau_0}\right) \cdot 100\% \quad (6)$$

Similarly, *RI* for the best found τ_{end}^* relative to the deterministic solution τ_{end0} can be calculated using Equation 7.

$$RI(\tau_{end}) = \left(1 - \frac{\tau_{end}^*}{\tau_{end0}}\right) \cdot 100\% \quad (7)$$

The algorithm consists of the sausage pre-smoking holding logistics model described in the second chapter, the Monte Carlo method implementation adapted for the sausage pre-smoking holding problem, as well as the tools to save and visualize the best solution found. The algorithm was implemented in Python 3.13.3. It can also check the feasibility of an instance, for example, whether it can be executed without overflowing the holding area. The Matplotlib 3.10.6 library was used to visualize the process and plot data describing algorithm performance. The visualization tool is presented in Figure 4. Output files containing the vectors **T**, **P**, **X**, **Y**, **T'**, **P'**, **X'**, **Y'**, and **C** were also generated.

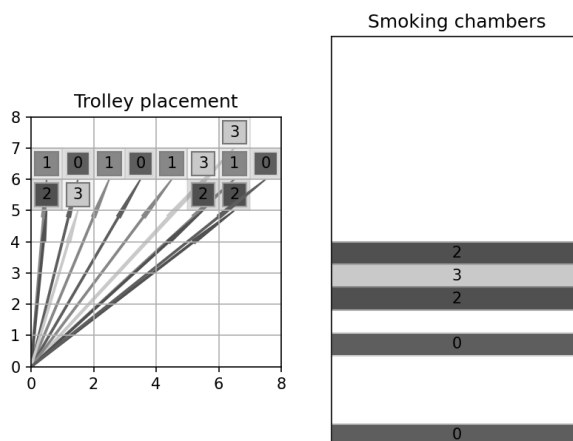


Figure 4. Trolley placement visualization tool

Source: own study.

The performance of the algorithm was measured based on the initial and optimized values of both objective functions (τ and τ_{end}), as well as their relative improvement. The influence of the previously described spatial and temporal parameters, as well as the number of epochs N , was assessed. The results were evaluated for three arbitrarily chosen feasible instances of varying complexity, with different values of spatial and temporal parameters, described in Table 3. For each parameter change, the solution was evaluated 100 times and then averaged arithmetically.

Table 3. Default instance parameters

Instance 1	Instance 2	Instance 3
$W = 8$ td $L = 8$ td $v_t = 0.2$ td/s $v = 2$ td/s $C = 18$ $l_c = 1.5$ td	$W = 10$ td $L = 10$ td $v_t = 0.5$ td/s $v = 4$ td/s $C = 18$ $l_c = 1.5$ td	$W = 12$ td $L = 12$ td $v_t = 1$ td/s $v = 8$ td/s $C = 18$ $l_c = 1.5$ td
Product temporal parameters (T_{pi} ; T_{di} ; T_{ri} ; T_{si}) [min.]: product 1: 10; 1; 30; 20 product 2: 10; 3; 30; 20 product 3: 10; 1; 20; 30 product 4: 20; 2; 45; 30 $T = 480$ min.	Product temporal parameters (T_{pi} ; T_{di} ; T_{ri} ; T_{si}) [min.]: product 1: 10; 1; 30; 20 product 2: 10; 3; 30; 20 product 3: 10; 1; 20; 30 product 4: 20; 2; 45; 30 product 5: 20; 2; 45; 30 product 6: 20; 2; 45; 30 $T = 480$ min.	Product temporal parameters (T_{pi} ; T_{di} ; T_{ri} ; T_{si}) [min.]: product 1: 10; 1; 30; 20 product 2: 10; 1; 30; 20 product 3: 10; 3; 30; 20 product 4: 10; 1; 20; 30 product 5: 20; 2; 45; 30 product 6: 20; 2; 45; 30 product 7: 20; 2; 45; 30 product 8: 20; 2; 45; 30 $T = 480$ min.

Source: own study.

3. RESULTS

Most of the time, the algorithm improved on the initial solution in the very first epoch, as the value of τ decreased in 92 of 100 runs in instance 1, 96 of 100 runs in instance 2 and in all 100 runs in instance 3. Different modifications to the above instances were considered, with a significant reduction in the holding area dimensions W and L causing the deterministic solution to be impossible to optimize using the Monte Carlo method. Minimization of τ sometimes resulted in an insignificant increase of τ_{end} , up to one minute. In most cases the minimization of τ_{end} also caused τ to decrease, but at a lower rate than when τ is chosen as the objective function. Optimization of τ_{end} occasionally caused τ to increase by up to 10 seconds. Certain combinations of parameters created outlying results, which persisted after multiple runs.

Figure 5 describes the relationship between the delays and the production timeframe. Figures 5a and 5c present the difference in total and end delays for different instances and timeframes, while Figures 5b and 5d describe the relative improvement and its standard error.

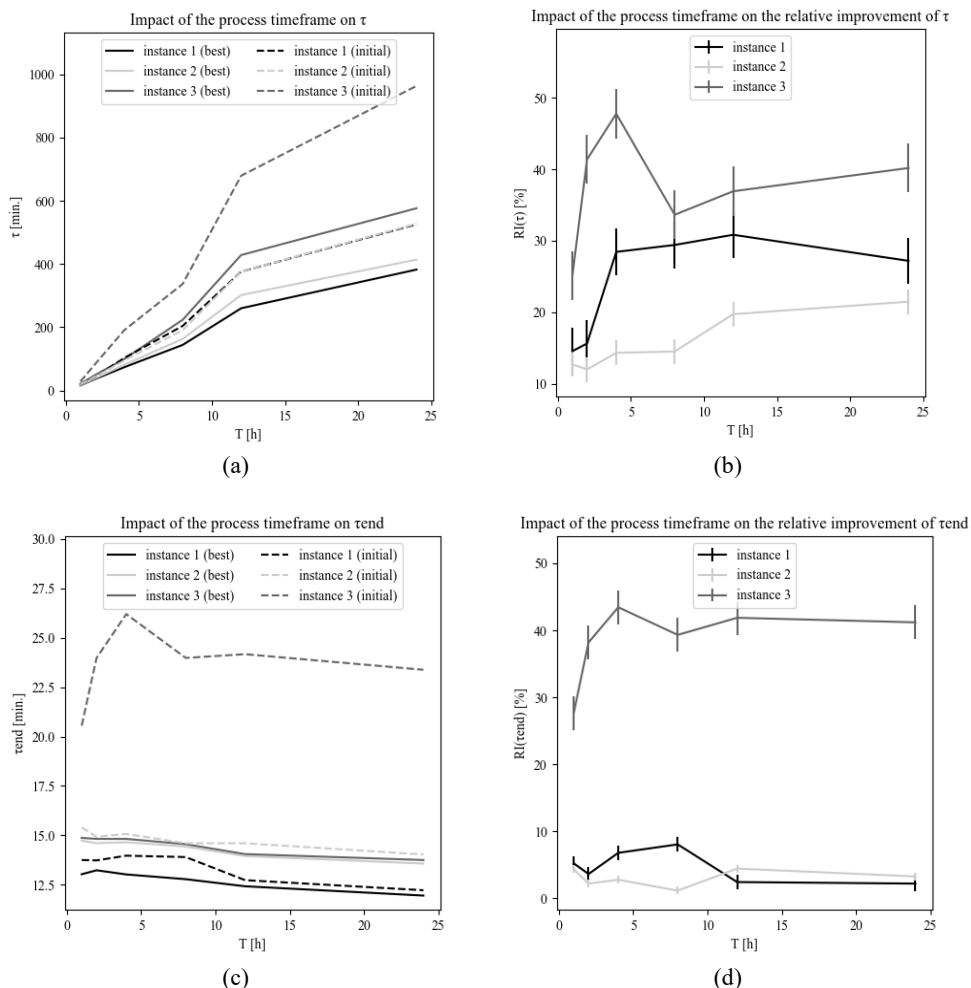


Figure 5. Absolute (a) and relative (b) impact of the production timeframe on τ , and absolute (c) and relative (d) impact of the production timeframe on τ_{end}

Source: own study.

In analyzing Figure 5a, it can be seen that longer production timeframe and large production volume contribute to the initial delay significantly, since more products bearing a similar delay risk are made. It can, however, be easily compensated for using

the algorithm considered (see Figure 5b). For $T = 4\text{h}$, the end delay of instance 3 was almost halved.

Figure 5c shows that longer production may lead to a slight decrease in the end delay. The results indicated that end delay could be hard to lower for smaller production volumes, but very easy for high-volume production, as seen in instance 3, where $RI(\tau_{end})$ stabilized at around 40%.

Figure 6 shows the relationship between different temporal technological parameters of the products considered. The changes were applied individually to the first product of instance 1. Figure 6a presents the absolute impact of these parameters, whereas Figure 6b describes the relative improvement of τ and its standard error.

In analyzing Figure 6a, it can be seen that longer dispatching linearly contributes to the sum of delays. Longer smoking time causes prolonged chamber unavailability, causing a sharp increase in τ . A decrease in production volume causes a slight decrease in delays, as less units bearing the risk of delay are made. The influence of holding time is insignificant. Figure 6b shows that delays induced by smoking are the easiest to minimize, especially for longer smoking times, followed by production and dispatch. Holding-induced delays are easy to minimize if the holding time is short ($T_{r,l} \approx 30\text{ min.}$), but it can be significantly harder to minimize delays if the holding time is long.

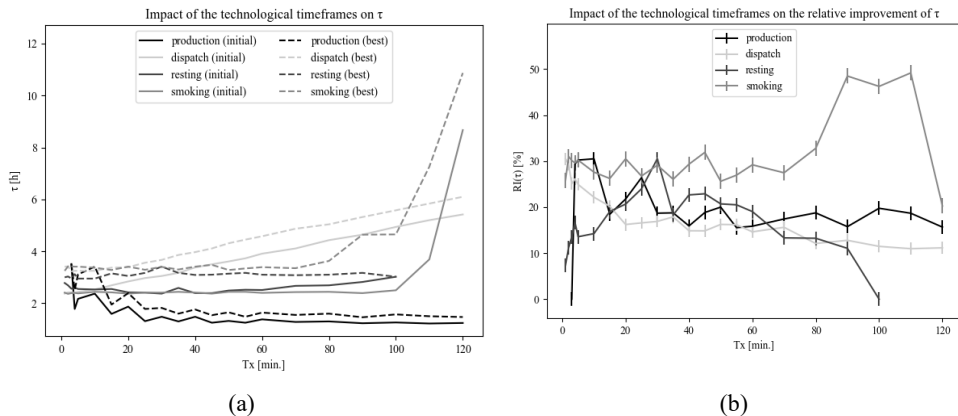


Figure 6. Absolute (a) and relative (b) impact of the temporal parameters on τ_{end}

Source: own study.

Figure 7 presents the impact of spatial plant setting parameters on the pre-smoking holding delays, τ . Figure 7a presents the difference in delay-induced quality losses for different area dimensions, Figure 7c for different operator speed values and

Figure 7e for different smoking area settings. Figures 7b, 7d and 7f describe the differences in relative units.

In analyzing Figure 7a, it can be seen that the increase in both the number of products and the holding area's dimensions causes longer transport times and ultimately an increase in delays. This is due to the need to cover longer distances. However, this can be easily corrected by the algorithm, as seen in Figure 7b.

Another factor contributing to pre-smoking holding delays is the operator speed. As seen in Figure 7c, trolley pushing and pulling speed v_t is a major factor. Insufficient speed combined with a larger volume of production can cause a significant increase in delays, as the time needed to cover the distance from the trolley's initial position to the smoking chamber is too long. Larger values of v and v_t do not necessarily decrease τ , however the increase of v_t can make optimization easier for larger volumes of production, as can be seen in Figure 7d.

In analyzing Figure 7e, it can be seen that an insufficient number of smoking chambers strongly increases the pre-smoking holding delays, because when all chambers are full, no new trolleys may be placed inside. The redundancy of the smoking chambers does not decrease the delay risk either, as more chambers are placed farther away. In fact, the spacing between the chambers is also a significant source of delays. In Figure 7f it can be observed that the algorithm can correct a significant part of the pre-smoking holding delays caused by the deficiency of smoking chambers. The delays resulting from l_c are harder to correct in more complex instances.

Figure 8 presents the impact of the same parameters on the end delay τ_{end} , where Figure 8a presents the differences for different pre-smoking holding area dimensions, Figure 8c for the operator speed values and Figure 8e for the smoking area settings. Finally, Figures 8b, 8d and 8f visualize the relative improvement. It can be seen that faster production by default increases the risk of a poorly synchronized finish, which can be corrected with the Monte Carlo method.

Figure 8a shows that a certain increase of the designated pre-smoking holding area width can decrease the initial end delay for more complex production plans. The algorithm, however, is potent enough to correct the delay by approximately the same amount, as can be seen in Figure 8b.

In analyzing Figure 8c, it can be seen that insufficient pushing and untooled operator speed may cause a slight increase in τ_{end} . As seen in Figure 8d, however, it can be easily compensated using the Monte Carlo method.

Figure 8e shows the impact of the number of smoking chambers and their spacing on the end delay. Similarly to the relationship between C , l_c and τ , the deficiency of free smoking chambers causes a longer end delay. As seen in Figure 8f, compensation of unfavorable spatial smoking chamber parameters is harder for larger production volume.

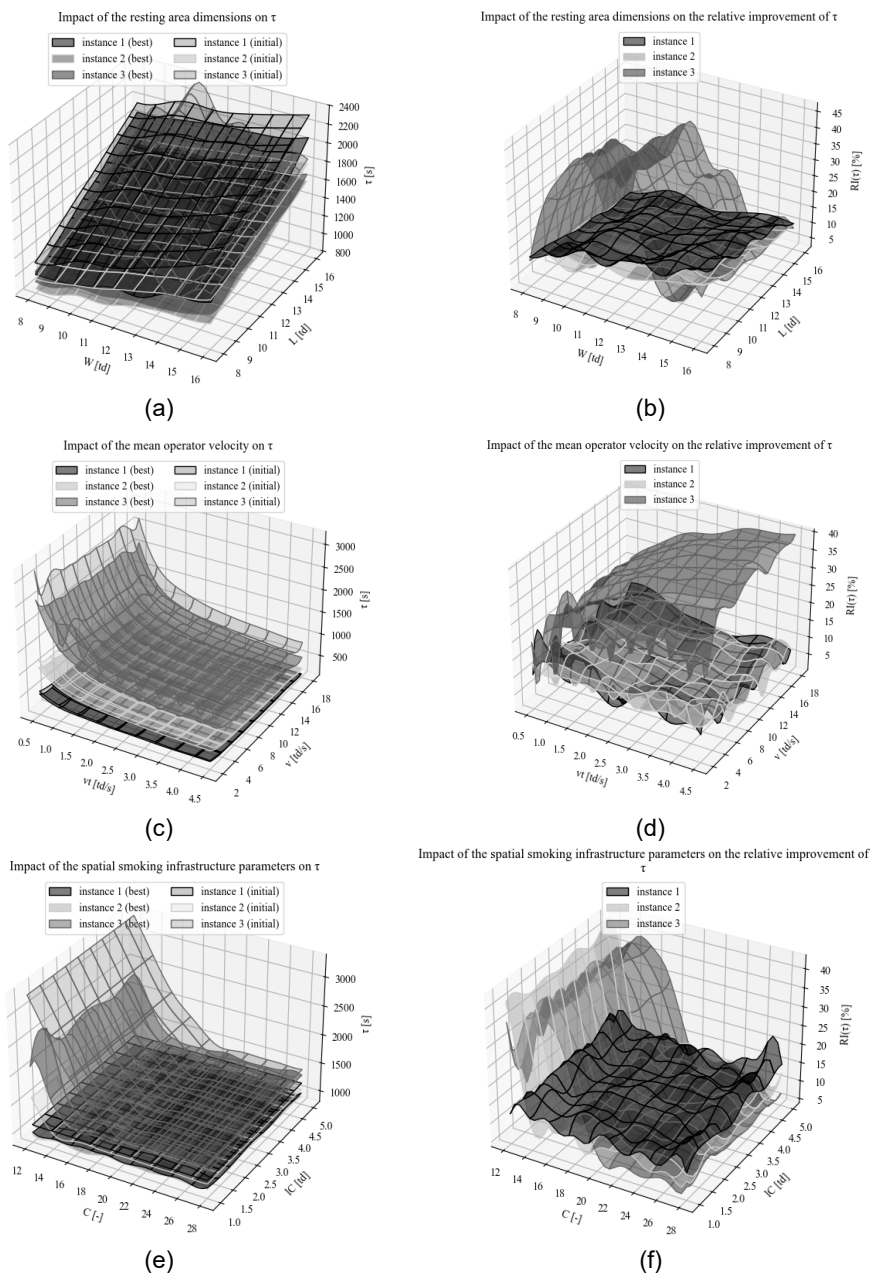


Figure 7. Absolute (a) and relative (b) impact of pre-smoking holding area dimensions, absolute (c) and relative (d) impact of operator speed, absolute (e) and relative (f) impact of smoking area layout on τ

Source: own study.

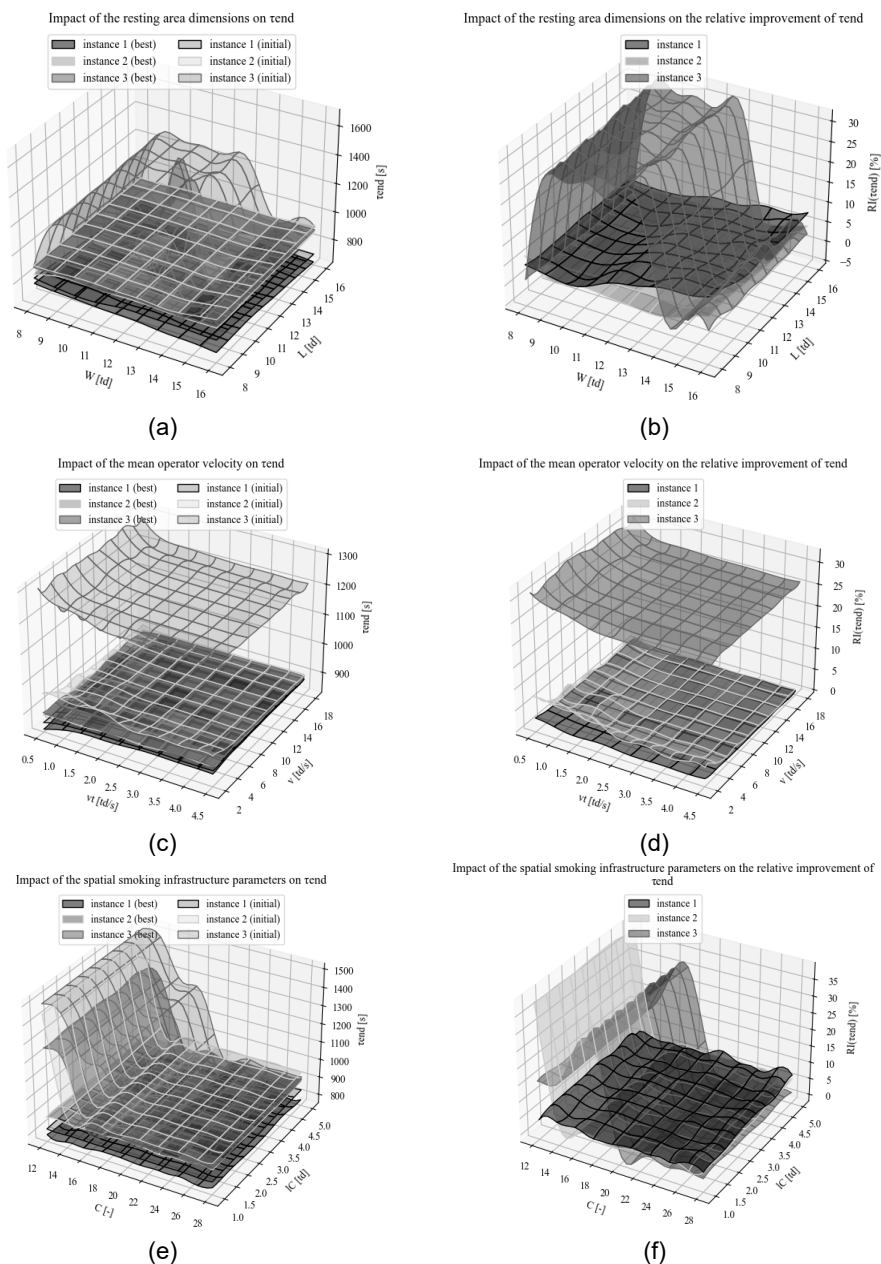


Figure 8. Absolute (a) and relative (b) impact of pre-smoking holding area dimensions, absolute (c) and relative (d) impact of operator speed absolute, and absolute (e) and relative (f) impact of smoking area layout on t_{end}

Source: own study.

Figure 9 shows the influence of the number of epochs on the relative decrease of pre-smoking holding delays, as well as the standard error. Figure 9a illustrates the relationship for τ and Figure 9b for τ_{end} .

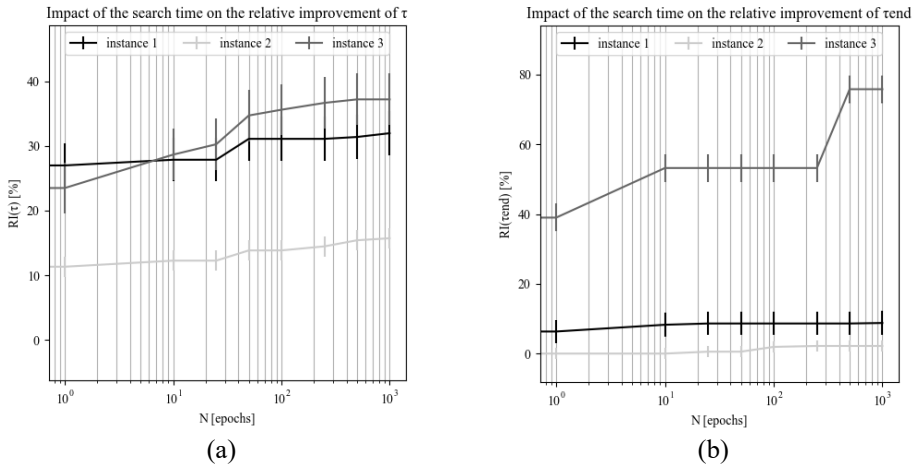


Figure 9. Relative impact of the number of epochs on τ (a) and τ_{end} (b)

Source: own study.

In analyzing Figure 9a, it can be seen that τ can be reduced by at least 10%, even for hard-to-optimize plans, such as instance 2. Delay reductions can happen after a very long time, such as at an average of $N = 569$ epochs for instance 3. The more complex the instance, the higher the relative improvement is. In Figure 9b it can be observed that τ_{end} for less complex instances is hard to minimize, but in the case of high-volume production, a prolonged search may increase the relative improvement to as much as $RI(\tau_{end}) = 76\%$.

The production plan complexity has a significant impact on execution time. The average algorithm execution speed (in 100 runs) was 1.72 epochs/s for instance 1, 1.23 epochs/s for instance 2, and 0.93 epochs/s for instance 3.

4. CONCLUSIONS

This paper presents the implementation of a stochastic optimization algorithm for the minimization of quality losses in the form of holding delays. Three arbitrarily designed feasible production plans were conceived for simulation and testing, considering the spatial and temporal characteristics of the process. The spatial parameters described the structure of the holding and smoking areas of a meat plant, as well as the statistical working speed of employees involved in the pre-smoking holding process. The

temporal parameters, on the other hand, were related to the technological characteristics found in sausage recipes.

The optimization algorithm used the Monte Carlo method, adapted for the sausage pre-smoking holding problem. The potency of the proposed algorithm was measured using absolute and relative units. The trolley placement simulation results demonstrated and quantified the influence of the parameters under consideration. Relative potency assessment results showed that in the case of high-volume and temporally asymmetric production plans, the proposed solution provided considerable improvement over grouping trolleys containing the same product. The stochastic optimization algorithm provided a relative delay reduction of around 10% for less complex production plans and up to 25–40% for high-volume production plans. The end delay was difficult to reduce significantly for low-volume production, but in case of more complex plans it was possible to reduce it by as much as 76%.

The presented optimization algorithm, as well as the I/O system, upon proper validation in a factory setting, could be applied to present instructions to the employees, and possibly autonomous transport robots and cobots. The basic data I/O system utilizing the file stream was used to load the list of parameters from a file and present the output in a different file. The output files contained the state vectors $\mathbf{T}$, $\mathbf{P}$, $\mathbf{X}$, $\mathbf{Y}$, $\mathbf{T}'$, $\mathbf{P}'$, $\mathbf{X}'$, $\mathbf{Y}'$ and $\mathbf{C}$, which could be used to replicate the optimized solution. This I/O system, combined with the conceived model and visualization tool, as well as possibly a hardware interface, could then be integrated into the sausage production infrastructure in meat plants.

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