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Mathematical Model for Production Scheduling and Deadline Compliance in the Sausage Industry

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Abstract. *The increasing complexity of production processes in the food industry requires advanced planning strategies to enhance efficiency and ensure timely order fulfillment. Challenges such as idle times, capacity constraints, and material waste can significantly impact production performance, making optimization essential for maintaining competitiveness. To address these challenges, this study develops a mathematical model based on Mixed-Integer Linear Programming (MILP) to optimize production scheduling and ensure compliance with delivery deadlines in sausage manufacturing. Implemented through an interactive dashboard in Excel with VBA, the model enables users to input product demand and target production dates, generating optimal solutions for synchronizing production stages and maximizing resource utilization. The results include precise calculations for the quantities required at each production stage, optimized start and end times, and an efficient allocation of products to available machines. Additionally, line and bar charts illustrate process times per area and product distribution, enabling the identification of bottlenecks and supporting strategic decision-making. The integration of Solver and VBA in Excel proves to be a cost-effective and adaptable solution to enhance competitiveness in high-demand environments with limited resources.*

Keywords-- *Mathematical Model, Optimization, Production Scheduling, Resource Allocation.*

I. INTRODUCTION

The global demand for food is influenced by factors such as population growth, economic development, and evolving consumption preferences, which vary across regions and countries [1],[2]. Projections indicate that between 2019 and 2050, the world's population will increase by approximately 26%, reaching 9.7 billion people. This rapid growth will exert significant pressure on food production systems, necessitating enhanced efficiency and optimization in the industry [3].

In Ecuador, the sausage industry has experienced substantial growth over the past decade, solidifying its position as a key sector within the national economy. With domestic consumption reaching 4.1 kg per capita per year, the industry plays a crucial role in the country's food production landscape [4].

For manufacturing companies, adaptive and precise planning systems are essential in dynamic production environments. Studies have demonstrated that the lack of integration between production planning and process control often results in unrealistic lead times and inefficient decision-making [5]. This underscores the necessity for more robust models incorporating predictive analytics and optimization techniques to enhance production efficiency [6]. Within the food industry, factors such as delivery deadlines, product quality, and optimal resource utilization are fundamental to maintaining competitiveness, making efficient production scheduling indispensable.

In the context of sausage manufacturing, various operational challenges arise due to the interdependence of key processes, including mixing, stuffing, oven cooking, and packaging. These processes introduce constraints that affect production efficiency and the ability to meet market demand. The primary challenges identified include compliance with delivery deadlines, capacity limitations, downtime, and material waste.

To address these challenges, mathematical optimization techniques, particularly linear programming using Solver in Excel, provide a viable solution. As noted by the author [7], Solver facilitates the development of optimization models that enhance resource allocation and production scheduling, ensuring adherence to critical constraints. A notable example of mathematical optimization in food production is its application in the dairy industry, where a scheduling model was successfully implemented to optimize yogurt production. This model determined optimal batch sizes and structured manufacturing schedules to minimize production times and reduce waste, demonstrating the effectiveness of mathematical programming in improving operational efficiency [8].

The primary objective of this study is to develop a linear programming-based mathematical model utilizing Solver in Excel to optimize production scheduling in a sausage manufacturing company located in Cuenca-Ecuador. The model aims to determine the optimal start and end times for production processes while ensuring the timely fulfillment of delivery deadlines. Additionally, it calculates the required quantities of each product type at every stage of production.

Designed as a decision-support tool for production management, the model is intended for use by personnel in companies operating similar production lines. By synchronizing production stages with delivery schedules while respecting operational constraints, the proposed model seeks to enhance efficiency, minimize downtime and waste, and address capacity limitations. Ultimately, this approach aims to strengthen the competitiveness of small and medium-sized enterprises in high-demand environments with constrained resources.

II. LITERATURE REVIEW

Efficient order assignment to machines is a critical factor in optimizing production within environments that operate under multiple constraints. Reference [9] address this issue in the context of uncertainty, proposing a mathematical model for order assignment in parallel machines with varying efficiencies. Their approach integrates an intelligent optimization algorithm and a scenario-generation method to enhance assignment processes in high-dimensional environments, considering order cancellations as a crucial variable. Similarly, Reference [10] investigate scheduling on a single machine with processing times and release dates dependent on various scenarios, addressing uncertainties such as transportation delays, machine failures, and workforce performance fluctuations. To tackle this NP-hard problem, they develop a branch-and-bound method with lower bounds, complemented by nine heuristics and an iterative population-based algorithm, demonstrating significant improvements in resource allocation efficiency and uncertainty management.

Multiproduct batch plant scheduling necessitates effective methodologies for order assignment and minimizing work-in-progress inventories. Reference [11] propose a two-stage approach for short-term scheduling in such environments. First, they cluster orders into batches, optimizing batch sizes and delivery dates to minimize inventory levels. Then, these batches are scheduled to efficiently meet established deadlines. Their mixed-integer linear programming-based model converges rapidly to near-optimal solutions using heuristic rules, proving its applicability to industrial challenges involving multiple production orders. Similarly, Reference [12] analyze batch sequencing in the bottling stage of soft drink production, employing subtour elimination constraints inspired by the Asymmetric Traveling Salesman Problem. Their comparative analysis of three methodologies, including a multicommodity flow-based formulation, demonstrates improved production sequencing but at the expense of increased computational complexity. These studies underscore the significance of advanced models in enhancing batch production efficiency and operational scheduling.

Mathematical models play a pivotal role in optimizing production within complex industrial environments, leading to increased efficiency and reduced operational costs. Reference [13] develops mixed-integer programming models aimed at minimizing total tardiness in hybrid flow shop systems with sequence-dependent setup times and blocking constraints. While effective for small-scale problems, their scalability is limited; hence, he proposes heuristics based on local search and evolutionary intelligence to solve larger instances efficiently. Similarly, Reference [14] optimize textile production by employing the Lot Sizing and Machine Speed model, which dynamically adjusts machine speeds to minimize costs and inventories. Due to the inherent complexity of the problem, they implement a two-phase heuristic based on iterative linear programming to derive optimal solutions within acceptable computational times. Additionally, Reference [15] introduce a hybrid genetic algorithm for hybrid flow shop scheduling, integrating greedy randomized adaptive search procedure for job assignment on parallel machines. Their methodology combines advanced heuristics with mixed-integer programming to minimize makespan and enhance efficiency in large-scale production systems.

Excel and Solver have emerged as practical optimization tools for addressing production challenges in various industrial settings. Reference [16] implement a user-friendly spreadsheet interface in Excel to solve permutation flow shop problems, minimizing makespan through mixed-integer programming, albeit with applicability limited to small-scale cases. Likewise, Reference [17] develop a decision support system in Excel for aggregate production planning, facilitating optimal resource allocation. Reference [18] leverage Excel's Solver and an evolutionary algorithm to solve Job Shop and Flow Shop Scheduling problems, optimizing completion times and makespan in a furniture manufacturing context. Reference [19] integrate mixed-integer programming with dynamic sequencing rules in an Excel-based model for hydraulic press planning in the automotive industry, achieving a 22.1% cost reduction. Furthermore, Reference [20] underscores the utility of Excel's Solver in solving linear programming models, while Reference [21] utilize Solver, Evolver, and Risk Optimizer to optimize a green supply chain, aiming to maximize profits while minimizing CO_2 emissions. These studies reaffirm the versatility of Excel and Solver in solving optimization problems related to production and logistics.

Recent research highlights the growing relevance of integrating simulation optimization methods into production scheduling processes. In this context, [22] conducted a systematic review on Simulation Optimization Applied to Production Scheduling (SOAPS), identifying key elements such as the use of discrete event simulation, optimization algorithms, and stochastic modeling to improve the responsiveness of production systems. Although their primary focus lies in high-tech manufacturing sectors, the methodological framework they propose is adaptable to other industries requiring synchronized, multi-stage production processes, such as food manufacturing. This reinforces the importance of incorporating operational constraints, set-up times, and real-time adaptability, aspects addressed in the mathematical model proposed in the present study.

The application of optimization models in aggregate production planning has proven crucial for enhancing operational efficiency and cost management within manufacturing sectors. [23] present a detailed study on the use of mixed-integer linear programming for optimizing aggregate production planning in a spinning textile company. The model was designed to identify the best combination of resources while estimating production costs, aiming to boost operational efficiency and cut overall expenses. Set within the context of the Latin American textile industry—particularly important in Peru—the study underscores the sector's susceptibility to disruptions like the COVID-19 pandemic, which had a severe impact on production capacity and employment levels. The proposed model integrated 48 constraints and 72 variables, covering critical areas such as workforce hiring and layoffs, standard and overtime production, inventory management, and handling production deficits. Results indicated an optimal aggregate plan cost of US $6,088,823, with US $5,663,774 allocated to raw materials and US $425,049 to associated production costs, including inventory maintenance, workforce adjustments, and overtime. The derived policy recommended strategic hiring and layoffs throughout the year, limited overtime use, and efficient inventory management to avoid deficits. Ultimately, the study reaffirms that mixed-integer linear programming models are effective tools for dynamic manufacturing environments, enabling adaptability to demand fluctuations and fostering competitiveness and sustainability in the textile sector.

Despite the effectiveness of these approaches in production optimization, they exhibit several limitations that impact their practical applicability in dynamic industrial settings. Many existing models overlook critical variables such as setup times, idle periods, and process losses, which are fundamental to operational efficiency. Moreover, reliance on computational tools with high processing power can hinder implementation in resource-constrained companies. Additionally, most studies fail to provide a comprehensive analysis of how decision-making in specific production areas influences the broader supply chain. In this context, the present study proposes a model that addresses these gaps by integrating key operational constraints and offering an adaptable optimization strategy suitable for various industrial sectors.

III. METHODOLOGY

This study follows a structured five-step methodology, as illustrated in Fig. 1. Each step systematically addresses the optimization of production scheduling in sausage manufacturing, ensuring a comprehensive approach to improving operational efficiency and resource utilization.

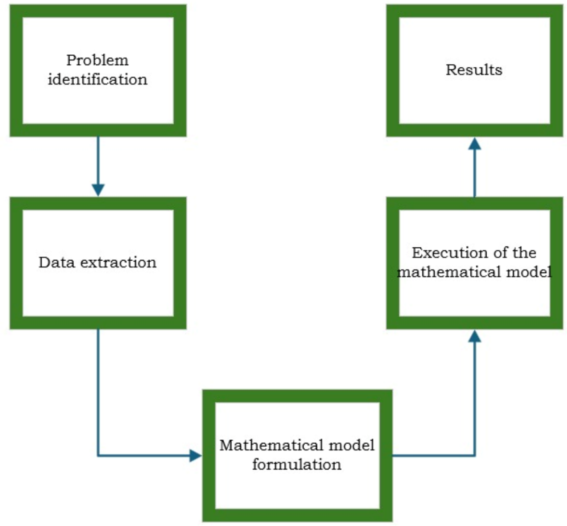


Fig. 1 Methodological steps implemented in the study

A. *Problem identification*

At this stage, the study focuses on identifying key operational challenges within the case study company's sausage production process. Four primary production areas were analyzed:

- Mixed
- Stuffing
- Oven Cooking
- Packaging

Through an in-depth operational analysis, the critical factors affecting on-time product delivery were identified. The main challenges detected include:

- Non-productive times: delays caused by machine setup, idle periods, and internal transport inefficiencies.
- Process waste: material losses occurring during machinery operations in each production area.
- Capacity constraints: machine productivity limitations, restricting overall production output.

B. *Data Extraction*

Data were collected during pre-professional practical hours conducted in the case study company, complemented by direct observation of production processes. The key information gathered includes:

- Production times per area and product: Covering the mixing, stuffing, oven cooking, and packaging stages.
- Machine capacities: Expressed in kg/min for each product type.
- Waste generation: Estimated percentages associated with processing in each machine.

C. *Mathematical Model Formulation*

The mathematical model was developed using MILP and solved with the Simplex method in Excel's Solver tool, recognized for its efficiency in solving linear programming problems with linear constraints. This approach enabled rapid iterations to identify optimal solutions.

- Objective function: minimize the total processing time required for each product from the mixing area to the packaging area while ensuring adherence to delivery deadlines.
- Constraints: incorporate limitations related to production requirements, machine capacity, setup times, idle times, transport times, process sequence, shared machinery usage, and material waste levels.

D. Model Execution

Once the mathematical model was formulated and validated, it was executed to address the identified production challenges. The model computed:

- The required quantity of each product at every stage of the process (mixing, stuffing, oven cooking, and packaging).
- The optimal start and end times for each operation.
- The machine processing times across all production areas for each product.
- Waiting times incurred due to machine availability and process synchronization.
- The total time each product remains in the production system.

E. Results

Finally, the results obtained were analyzed to assess their accuracy and practical implications. This evaluation facilitated the identification of potential improvements, allowing adjustments to be made to enhance the model's effectiveness based on the company's specific needs.

IV. DEVELOPMENT OF THE MATHEMATICAL MODEL

In the manufacturing process of the case study company, several critical factors affecting product delivery times were identified. Key issues include downtime, process waste, and capacity constraints. This study focuses on three primary products: Viennese sausage, special mortadella, and hot-dog sausage. Based on data gathered through pre-professional practices and direct observation, the production process was analyzed across its different stages: mixing, stuffing, oven cooking, and packaging. The objective is to optimize these processes and minimize production times at each stage.

Table 1 links the products to the machines required for their production, while Fig. 2 presents a thread diagram illustrating the process flow. This visual representation facilitates a better understanding of the system's interactions and helps identify potential areas for improvement.

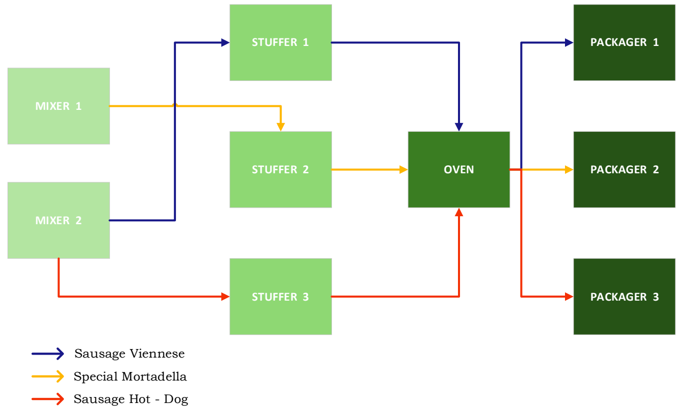


Fig. 2 Diagram of threads of the case study company

TABLE I
MACHINES REQUIRED BY PRODUCTS

Products / Machines	*Sausage Viennese*	*Special Mortadella*	*Sausage Hot - Dog*
Mixer 1		X	
Mixer 2	X		X
Stuffer 1	X		
Stuffer 2		X	
Stuffer 3			X
Oven	X	X	X
Packager 1	X		
Packager 2		X	
Packager 3			X

For the development of the mathematical model, MILP was employed. The model was structured as follows:

1. Sets

Sets provide an organized representation of the variables, parameters, and constraints within the model. The sets used are detailed in Table 2.

TABLE 2
SETS OF MATHEMATICAL MODEL

i: *Process area*	j: *Types of products*
$i = 1 : Mixing$ $i = 2 : Stuffing$ $i = 3 : Baking$ $i = 4 : Packaging$	$j = 1 : Sausage\ Viennese$ $j = 2 : Special\ Mortadella$ $j = 3 : Sausage\ Hot - Dog$

2. Parameters

Parameters represent fixed data that remain constant throughout the model. These values serve as the foundation for calculations and aid in evaluating potential solutions. The parameters used in the model are outlined in Table 3.

TABLE 3
PARAMETERS OF THE MATHEMATICAL MODEL

Default Parameters	
$Capacity_{ij}$	$Processing\ capacity\ of\ area\ i\ for\ product\ j\ (kg/min)$
$TSetUp_{ij}$	$Setup\ time\ of\ area\ i\ for\ product\ j\ in\ minutes$
$Tidle_{ij}$	$Idle\ time\ of\ area\ i\ for\ product\ j\ in\ minutes$
$T\_transport_{ij}$	$Transport\ time\ from\ area\ (i-1)\ to\ area\ i\ for\ product\ j$
$Lost_{ij}$	$Percentage\ of\ loss\ in\ area\ i\ for\ product\ j$
$Base\ date$	$Current\ date\ in\ time$
Input parameters	
$Delivery\_Time_j$	Date by wich product j must be completely produced
$Demand_j$	$Final\ cuantity\ required\ of\ product\ j\ (kg)$

3. *Decision variables*

Decision variables, see Table 4, define the model's key components, representing quantities that can be adjusted to achieve optimal results while adhering to system constraints.

TABLE 4
DECISION VARIABLES OF THE MATHEMATICAL MODEL

Q_{ij}	$Processed\ cuantity\ of\ product\ j\ in\ area\ i\ (kg)$
$TimeStart_{ij}$	$Start\ time\ of\ product\ j\ in\ area\ i\ (in\ minutes\ from\ base\ date)$
$EndTime_{ij}$	$Finish\ time\ of\ product\ j\ in\ area\ i\ (in\ minutes\ from\ base\ date)$

4. *Objective Function*

The primary goal of the model is to minimize the total production time required to fulfill orders. This objective ensures that production processes are optimized to align with the company's operational goals and resource constraints.

$$\min Z = \sum_{j=1}^{J} EndTime_{4j} - TimeStart_{1j} \quad (1)$$

5. *Constraints*

Constraints define the system's limitations, ensuring that the proposed solutions are feasible and respect operational conditions.

- Demand Fulfillment Restriction

The quantity processed in the packaging area (i=4) must be sufficient to meet final demand, accounting for accumulated losses:

$$Q_{4j} = Demand_j * (1 + Lost4j) \quad (2)$$

For the above areas (i<4)

$$Q_{ij} = Q_{(i+1)j} * (1 + Lost_{ij}) \quad (3)$$

- Process Sequence Restriction

The start time in each production area must be greater than or equal to the end time in the previous area, considering the required transport time between stages:

$$TimeStart_{ij} \geq EndTime_{(i-1)j} + T_{transport_{ij}} \quad (4)$$

- Start and End Time Restriction

The end time of an area is determined by the start time, setup time, effective processing time, and idle time, ensuring an accurate calculation of production scheduling constraints:

$$EndTime_{ij} \geq TimeStart_{ij} + \frac{Q_{ij}}{Capacity_{ij}} + TSetUp_{ij} + Tidle_{ij} \quad (5)$$

- Restriction on Compliance with Dates

To ensure that each product is completed before its designated delivery date, a time constraint is imposed based on the scheduled end time of each product in the final processing stag

$$EndTime_{4j} \leq \text{Minutes From Base Date}_j \quad (6)$$

- Minutes From Base Date:

Calculates the minutes elapsed from a predefined base date (model day 0) to the specified delivery date, allowing accurate scheduling adjustments.

$$(Delivery\_Time - Base\ date) * 1440 \quad (7)$$

Where 1440 are the minutes in a day.

- Machine Sharing Restriction

For mixer 2:

$$(TimeStart_{11} \geq EndTime_{13}) \quad (8)$$

For Oven:

$$(TimeStart_{32} \geq EndTime_{31}) \quad (9)$$

$$(TimeStart_{33} \geq EndTime_{32}) \quad (10)$$

V. ANALYSIS OF RESULTS

Once the mathematical model was fully implemented, it was executed to address the production scheduling problem effectively.

Initially, an interactive dashboard with a user form (USERFORM) was developed in VBA within Excel, allowing users to input key production planning data. This included the specific demand for the three products—Viennese sausage, special mortadella, and hot-dog sausage—as well as the target date for production completion, as illustrated in Fig. 3. The interface was designed to streamline data entry while ensuring that the mathematical model's constraints and calculations align with the company's operational requirements. By leveraging this system, production processes were optimized, and compliance with established delivery deadlines was effectively managed.

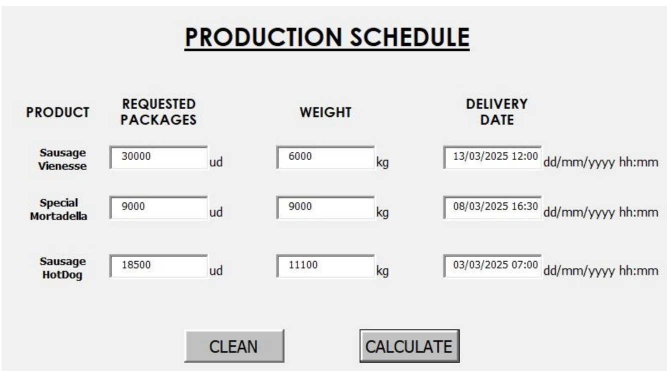
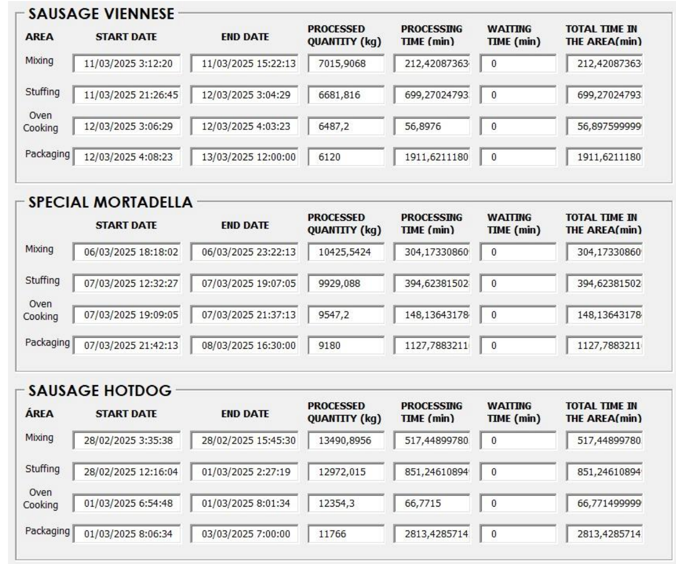


Fig. 3 Data Entry Interface

Following the execution of the model, the obtained results, depicted in Fig. 4, provided precise calculations regarding the exact quantities required for each product at every stage of the production process, including mixing, stuffing, oven cooking, and packaging. Moreover, the optimal start and end times for each operation were determined, facilitating the synchronization of activities and significantly reducing non-productive times. Additionally, the model identified operating times for the machines in all production areas and quantified the waiting times caused by machine availability constraints. Furthermore, the model estimated the total duration each product remained within each stage, offering a holistic view of the production flow and enabling more efficient resource allocation and operational planning.

These findings align with previous research, such as the study by Reference [24], which demonstrated that structured production planning and control contribute to enhanced resource utilization, minimized idle times, and improved synchronization of activities within manufacturing systems. Additionally, their investigation reinforces that effective production planning is essential to align demand with supply while maintaining high levels of operational efficiency.



SAUSAGE VIENNESE

AREA	START DATE	END DATE	PROCESSED QUANTITY (kg)	PROCESSING TIME (min)	WAITING TIME (min)	TOTAL TIME IN THE AREA(min)
Mixing	11/03/2025 3:12:20	11/03/2025 15:22:13	7015,9068	212,42087363	0	212,42087363
Stuffing	11/03/2025 21:26:45	12/03/2025 3:04:29	6681,816	699,27024793	0	699,27024793
Oven Cooking	12/03/2025 3:06:29	12/03/2025 4:03:23	6487,2	56,8976	0	56,897599999
Packaging	12/03/2025 4:08:23	13/03/2025 12:00:00	6120	1911,6211180	0	1911,6211180

SPECIAL MORTADELLA

	START DATE	END DATE	PROCESSED QUANTITY (kg)	PROCESSING TIME (min)	WAITING TIME (min)	TOTAL TIME IN THE AREA(min)
Mixing	06/03/2025 18:18:02	06/03/2025 23:22:13	10425,5424	304,17330860	0	304,17330860
Stuffing	07/03/2025 12:32:27	07/03/2025 19:07:05	9929,088	394,62381502	0	394,62381502
Oven Cooking	07/03/2025 19:09:05	07/03/2025 21:37:13	9547,2	148,13643178	0	148,13643178
Packaging	07/03/2025 21:42:13	08/03/2025 16:30:00	9180	1127,7883211	0	1127,7883211

SAUSAGE HOTDOG

ÁREA	START DATE	END DATE	PROCESSED QUANTITY (kg)	PROCESSING TIME (min)	WAITING TIME (min)	TOTAL TIME IN THE AREA(min)
Mixing	28/02/2025 3:35:38	28/02/2025 15:45:30	13490,8956	517,44899780	0	517,44899780
Stuffing	28/02/2025 12:16:04	01/03/2025 2:27:19	12972,015	851,24610894	0	851,24610894
Oven Cooking	01/03/2025 6:54:48	01/03/2025 8:01:34	12354,3	66,7715	0	66,771499999
Packaging	01/03/2025 8:06:34	03/03/2025 7:00:00	11766	2813,4285714	0	2813,4285714

Fig. 4 Mathematical model results interface

As part of the visual analysis, two key graphical representations were generated to assess the model's performance. The first, a line graph (Fig. 5), illustrates the process times across each production area, enabling a visual identification of bottlenecks and critical stages in the workflow. The second, a combined horizontal bar graph (Fig. 6), depicts the product allocation across different machines, showcasing the efficient utilization of available resources and the operational capacity of each piece of equipment. These graphical outputs facilitate the interpretation of data, assisting decision-makers in formulating strategic adjustments to optimize production processes and ensure strict adherence to delivery schedules.

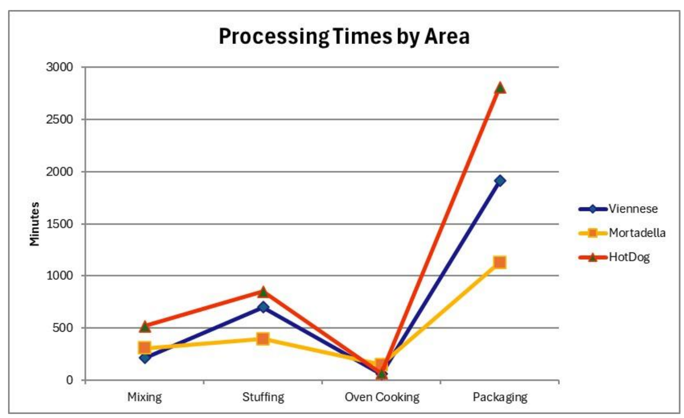


Fig. 5 Line graph

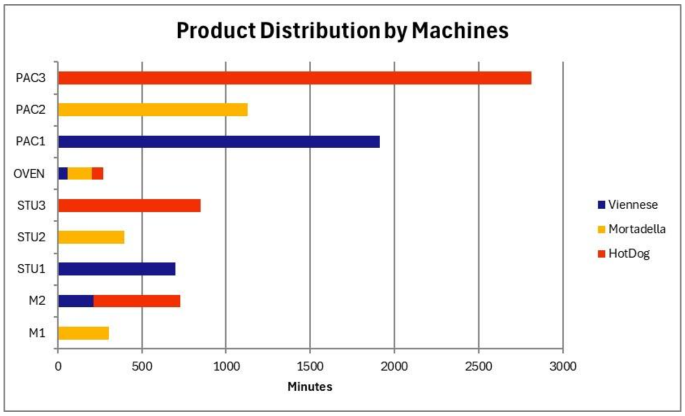


Fig. 6 Combined horizontal bar graph

VI. CONCLUSIONS

The development of the mathematical model successfully optimized production processes by ensuring compliance with delivery deadlines, synchronizing production stages, and reducing non-productive times. The model facilitated an efficient allocation of products to machines, maximizing operational capacity, minimizing idle times, and improving the utilization of available resources.

This model was specifically designed for a sausage production company in Cuenca, Ecuador, targeting small and medium-sized enterprises (SMEs) with limited resources and machinery. The results, presented through line and bar graphs, provided a comprehensive visualization of the production flow, enabling the identification of bottlenecks and supporting strategic decision-making. Furthermore, the implementation of VBA and Solver in Excel demonstrated to be an adaptable and effective solution for addressing the specific constraints of the food industry, establishing a replicable framework that enhances competitiveness in high-demand environments with limited resources.

To further enhance the model's effectiveness, future research could incorporate binary decision variables to optimize product-to-machine allocation. Additionally, integrating cost-related parameters could expand the model's potential to maximize operational efficiency and economic benefits. Another promising approach to improve production sequencing involves the implementation of heuristic sequence search procedures.

According to Reference [25], he heuristic procedure they reformulated—based on the Wagner and Davis method—enables the development of complex sequences for different product batches. This enhancement would allow the model to support strategic resource allocation, aiming to minimize unnecessary production and maximize machine utilization.

By implementing these improvements, the proposed optimization framework could evolve into a more sophisticated tool capable of supporting dynamic production environments in the food processing sector and beyond.

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