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A Lean Six Sigma Approach to Reducing Waste in Flour and Pasta Production

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Abstract

Food waste is a problem that transcends continents and generations, costing trillions of dollars. This case focuses on reducing food waste in X company's long pasta production process using Lean Six Sigma (LSS) methodologies. The study provides a step-by-step comprehensive approach to problem definition, analysis and solving utilizing process flow, Statistical Process Control (SPC), multiple fishbone diagrams, regression analysis, and Design of Experiments (DoE). The standardized speed settings approach was chosen through alternative comparison (Pugh matrix), which significantly dropped the ratio of waste to production from 19.0% in the control group to 10.0% in Experimental Group 1, 14.5% in Experimental Group 2, and 13.1% in Experimental Group 3. For direct material loss only, the annual cost saving of the improvements is expected to be ~82 k JOD/year (≈ $116 k/year). The study highlights that sustained monitoring and involvement of employees are crucial for sustaining the improvements. The company is highly encouraged to implement the second and third viable alternatives suggested and to train employees on the new principles and technologies towards cleaner production. Finally, our findings directly support several United Nations Sustainable Development Goals (SDGs): SDG 12 (Responsible Consumption and Production), SDG 2 (Zero Hunger), and SDG 13 (Climate Action).

Keywords: Lean Six Sigma (LSS), Waste reduction, Alternatives selection, Design of experiments, Pasta production, Cost saving.

1. Introduction

The industrial sector is a pivotal building block in the Jordanian economy. According to the Jordan Chamber of Industry (JCI), this sector contributes about 25% of Jordan's total Gross Domestic Product (GDP) and employs 245,000 workers. Its role is to promote the economic development process and solve many economic problems that the Jordanian economy suffers from [1].

Food manufacturing is important to Jordan's economy in order to attain GDP growth, jobs, and poverty reduction. This sector encompasses the production of food, agricultural industries, and essential supplies. The gross output of food manufacturing ranks first at 22.5% among 10 industrial subsectors. According to the Jordan Strategy Forum (JSF), the sector's local sales reach 86.6%. Regarding its interrelations and magnitude of the multiplier, the food industry comes first when considering the total multiplier (Direct and indirect impact) at 2.550 per Jordanian Dinar (JOD) spent in this sector. This confirms its position as a pillar for economic growth and sustainability [2].

X Group was founded in 1949 as one of Jordan's oldest and most diversified cereal processors. Headquartered in Amman, X owns and operates a wheat flour mill, a pasta plant, a snack foods and breakfast cereals plant, and a bakery ingredients production and distribution operation. Certified ISO9001 and ISO22000, the company has over 400 employees and an annual turnover above USD 30 million [3]. The portfolio of X includes different types of flours-semolina, pasta products, specialty flours, bread mixes and improvers, cake mixes, and snacks. Twenty years after its establishment, X launched an iconic brand with a daily production rate exceeding 100 metric tons during that period, with a strong local and regional distribution network.

The primary challenge facing X Group is the high defect rates in the production of long pasta. According to the latest quality department reports, the factory has been experiencing significant waste, both manufacturable and non-manufacturable, during the long pasta manufacturing process between January and October 2024. Manufacturable waste typically includes materials that fall or spill (from the hanging stands through the travel network) within the closed production systems, including pre-drying, drying chambers, cooling and storage. However, non-recyclable wastes include everything that falls on the floor (outside the closed system), in addition to dough scraps. For the long pasta, the manufacturable defects amount to +1.5 tons per day, against a good production of 10.67 tons per day—a defect rate of nearly 13%. Additionally, non-manufacturable waste stands at 0.79 tons per day. In stark contrast, the defect rates for short

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pasta production are considerably lower. The manufacturable waste for short pasta is 7 kg per day, and the non- manufacturable is 126 kg per day. This significant disparity highlights inefficiencies and issues specific to the long pasta production process.

For long pasta, regrinding the manufactured waste, storing it, preparing it and distributing it into batches within the next production is time-consuming and effort-consuming. Due to the large volume of market demand and the considerable amount of food waste, the production team works three shifts (24 hours) except for the final packaging, which works one shift only.

Additional resulting challenges include decreased operational flexibility, the rise of quality concerns, and the added pressure on the quality team, who may be forced to work more than a single shift. Looking at the non-manufacturable waste of approximately +0.5 tons per day, despite the opportunity to utilize/sell it to other industries, it is still a loss in financial and environmental terms.

The purpose of the study is to improve high defect rates in the production of long pasta through the Lean Six Sigma (LSS) discipline. In particular, specific objectives of the study are:

- To apply the techniques of LSS, including Statistical Process Control (SPC), to monitor the production processes
- To identify the root causes of high waste rates in the long pasta production process
- To propose and implement solutions to the problem and test their effectiveness

This study advances LSS practice and evidence in food manufacturing in multiple ways. First, we formalize and consistently employ a production-normalized waste metric (waste-to-production ratio) so that control-charting, modeling, and experimentation remain robust to throughput changes across shifts and months. Second, we demonstrate a sequenced integration of SPC (I/MR) → multi-fishbone RCA → regression screening → Pugh decision matrix → DoE validation, executed on a live long-pasta line—a context with distinctive geometry- and handling-induced defects often overlooked relative to short-cut lines. Third, we move beyond association to actionable control by isolating hanging-stand speed as the statistically significant lever and encoding it into a standardized speed policy that is load-aware (low/medium/high). Fourth, we provide field-verified improvements achieved without major capex, highlighting a scalable path to SDG-12.3 targets in resource-constrained plants.

A brief synthesis of the literature gaps and our contributions is provided at the end of the Literature Review (Section 2), situating this work within food-manufacturing LSS research.

2. Literature Review

2.1. Food Waste in the Food Manufacturing Industry

Food waste in food production is a problem that affects the entire world, with many far-reaching economic, environmental, and social consequences. This section sets the wider context of the issue.

The Food and Agriculture Organization (FAO) estimates that one-third (around 1.3 billion tons) of the food produced for human consumption gets either lost or wasted globally each year [4]. Based on recent estimates, this can feed 1.26 billion hungry people annually. This adds to increasing Greenhouse Gas (GHG) emissions (8-10% of global GHG) and resource depletion [5]. While post-harvest losses and consumer waste contribute substantially, the food manufacturing sector plays a significant role in this issue.

More recent estimates that place a greater emphasis on food waste are particularly hard to quantify in manufacturing due to the varied definitions, different practices of data collection, and reporting standards that exist across countries and industries [6]. Current studies using more detailed data and superior modeling techniques provide a clearer picture. A study by [7] has indicated that most of the supply chain food loss, especially that of perishable products, happens at the processing level or during its packaging. Within the EU, food loss within manufacturing accounts for 39%, while critical stages of food wastage include agricultural production at 413 MT, postharvest handling at 293 MT, processing at 148 MT, distribution at 161 MT, and consumption at 280 MT. Food wastage reduction offers the potential for an enabling role within the water–energy–food nexus [8].

The economic impact of food waste is large. The direct costs entail the loss of raw materials, energy, water, and labor invested in the production of the wasted food [9], while the indirect costs entail the loss of revenue due to unsold products, fees related to the disposal of wasted products, and damage to the brand reputation [10]. According to the [11] in Europe alone, food waste is estimated to cost about 143 billion euros annually, and this affects various sectors. Moreover, embedded waste within food, like water and energy, is considered an economic loss at both the company and national level [5]. To reduce the costs of food waste, [12] implemented a real-time Internet of Things (IoT) based food waste tracking system in a ready-meals factory, achieving a significant 60.7% reduction in waste over nine months, equating to approximately £306,873 in cost savings. [13] used 10 descriptive case studies of Italian food manufacturers and refined the "food waste hierarchy" by identifying key strategies like structured surplus food control systems and partnerships.

On the ecological level, decomposing food waste in the landfill produces methane, a very active GHG, which is more poten than one order of magnitude in its global warming potential compared to carbon dioxide [14]. Large volumes of water and land resources are used in the manufacturing of food that eventually gets wasted, adding to water scarcity and deforestation. Therefore, the circular economy provides an enabling framework for addressing food waste within the manufacturing context. [15] found that avoidable food waste has environmental costs ranging from 2000 to 3600 kg CO_2-eq per tonne, 2400 to 4700 kg of water depletion per tonne and significant fossil resource depletion (11,000–21,000 MJ per tonne). [16] reported that the anaerobic treatment of 200 tons of food waste in Beijing provides a benefit of 66,888 Chinese yuan, produces 43,350 kWh of electricity and reduces 16,087 kg of CO_2 emission. System dynamics has been used as an effective tool to forecast CO_2 emissions and other ecological determinants, which can be expanded to the prediction of the effect of food waste [17, 18].

In response to the increasing challenges, several national and international initiatives have targeted reducing food waste throughout the food supply chain, including the manufacturing sector. The United Nations Sustainable Development Goal (UN-SDG) 12,3 calls "To, by 2030, halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses" [19]. The European Union has adopted a Farm to Fork Strategy that defines reduction targets for food waste at every step in the food supply chain [20]. The following section will explore the methodologies and tools used to address this challenge, focusing on Lean and Six Sigma principles.

2.2. Integration of Lean and Six Sigma (Lean Six Sigma-LSS)

LSS is a very powerful synergistic approach to process improvement. Lean mainly deals with eliminating waste (Muda) and streamlining processes [21]. while Six Sigma focuses on reducing variability and attaining near-perfect quality. It employs the DMAIC (Define, Measure, Analyze, Improve, Control) cycle as an orderly problem-solving platform [22]. Together, they create a formidable platform for continuous improvement.

The most diffused basis of LSS project performance is the DMAIC cycle originating from Six Sigma. In the case of LSS, the DMAIC cycle is often complemented with Lean tools and methods. In the Define phase, the problem is unequivocally identified, the project's goals are set, and the scope of the improvement project is determined. In the Measure phase, data collection is realized to understand the process's current performance. Measurement system analysis is performed to ensure the data obtained is accurate and reliable. The statistical tools and techniques in the Analyze phase are employed to understand the root cause of the defects and variation. Common tools during this phase include 5 Whys, fishbone diagrams, hypothesis testing, and regression analysis. The Improve phase includes developing and implementing solutions to address the root causes identified in the analysis phase. Finally, the Control phase aims to maintain the improvements established during the previous phases [23].

LSS has been successfully implemented in various manufacturing sectors, significantly improving quality, efficiency, and cost reduction. The following section highlights its application in the food industry.

2.3. LSS Applications in the Food Industry

Compared with other manufacturing industries, there are many unique challenges to implementing LSS in the food industry. First, the highly perishable nature of most food products requires strict control of temperature, humidity, pressure, and processing time to maintain quality and safety [24]. Second, strict food safety regulations such as HACCP and ISO 22000 require meticulous documentation and traceability [25]. Third, many raw materials and final products in the food industry are intrinsically variable because of their size (for example, long and short pasta), shape, composition, and other characteristics. This may strongly affect process performance and product quality, hence requiring robust process control interventions using LSS methodologies.

Several literature studies and cases show the potential application of LSS in food industries of different segments. [26] discussed how food industry characteristics lead to variations in the adoption and performance impact that arises from practices related to the adoption of LSS. A total of 145 responses to a survey from food firms were analyzed using structural equation modeling. LSS was found to influence financial gains and product quality positively; however, low familiarity, cost constraints, and the complexity of statistical techniques impede the diffusion. [27] introduced the integration of LSS as a waste reduction methodology in the manufacturing processes of food products. The use of the DMAIC approach effectively evaluated and reduced waste, which had actionable suggestions for process improvement. [28] study involved developing and validating multi-item measurement scales for the LSS competence that merges flow improvement from Lean with structured problem-solving from Six Sigma. The instrument is applied herein to the food industry to determine what practices are being followed by the LSS and to bring out improvement opportunities. In juice and beverage processing lines, LSS has improved process cycle efficiency from 15.28% to 34.05% and reduced lead time. These optimizations' projected annual economic benefit was 2.13 million USD [29]. Furthermore, [30] applied LSS in a medium-sized confectionery to reduce overfilling and rework, focusing on its gingerbread production. Elimination of variability and waste using the technique brought significant cost savings. Despite LSS effectiveness and previous successes, [26] called for more investigation in the food industry due to vast uncertainties. To provide a more comprehensive overview of LSS applications in the food industry, a summary of key studies is presented in Table 1.

2.4. Gaps Addressed by This Study

Prior work highlights the scale and measurement challenges of food-waste analytics in manufacturing—definitions and data practices vary widely across sites and countries, complicating comparability and inference. At the same time, processing/packaging stages account for a substantial share of losses along the food chain, underscoring the need for plant-level, process-improvement evidence. In the LSS literature for food, many contributions are survey-based (linking "LSS practices" to performance) or descriptive cases, with relatively fewer factory trials that couple statistical screening with experimental validation.

This study addresses these gaps in four ways. First, we use a production-normalized KPI (waste-to-production ratio) throughout analysis to mitigate throughput heterogeneity, enhancing comparability across shifts and loads under real operations. Second, we present an end-to-end DMAIC tool-chain (SPC, root-cause analysis, regression screening, Pugh selection, DoE) executed in-plant, thereby moving beyond cross-sectional association to causal validation of a specific actuator (standardized hanging-stand speed policy). Third, we contribute domain-specific evidence from a thermally dried long-pasta line, where defect mechanisms and waste profiles differ markedly from short-pasta operations—an area underrepresented in detailed operational studies. Fourth, we report field-verified effects across load tiers (low/medium/high), demonstrating the transferability of a low-capex intervention under realistic throughput variation.

3. Methodology

The study applies a systematic LSS approach to finding and reducing waste in X Group's long pasta production process. LSS combines Lean manufacturing methods, which focus on waste reduction, with Six Sigma strategies, which intend to minimize defects or process variability in manufacturing [28]. This hybrid methodology is effective within scenarios of food production where both issues of waste reduction and improvement in quality become vital [26].

The roadmap starts by reviewing the literature to explore the recent LSS methods and tools used in the same settings. Then, it moves to applying the DMAIC roadmap. Prior to analysis we evaluated alternative improvement logics—DMAIC, DMADV/DFSS, PDCA/A3, and 8D—against the project's characteristics: (a) existing long-product drying line with measurable scrap/waste; (b) unknown primary drivers; (c) ability to collect time-series data and run designed experiments without capital changes; (d) need for sustained control across shifts after implementation. DMAIC best satisfies these criteria because it explicitly couples statistical diagnosis (e.g., SPC, regression) and experimental validation (e.g., DoE) with a Control phase that institutionalizes the solution (SOPs, control plans, and ongoing charting). In contrast, DMADV/DFSS targets new designs or transformative re-engineering; PDCA/A3 is effective for incremental cycles but offers weaker guidance on inferential statistics; and 8D excels at acute defect containment and team actions rather than long-horizon process stabilization.

Once the problem is defined clearly, the measurement phase takes place through the data collection phase. The production data, waste records, and quality control reports are collected from August to October 2024 due to the availability of data for all the measures incorporated. In the analysis phase, root cause analysis tools such as Fishbone diagrams and Pareto charts are utilized to find the causes of defects and inefficiencies. The improvement phase identifies and implements solutions to these causes before moving to the control phase, where new processes are monitored for continued compliance and improvement. Besides the Six Sigma roadmap, the Lean methodologies are implemented to eliminate waste in the long pasta production processes at X Group. This ensures a concerted effort on all levels of the production line to ensure efficiency.

3.1. Data Collection Methods

Data collection in this study was meticulously undertaken to ensure that detailed and accurate information was obtained to help observe and analyze the problem. Qualitatively, the production manager ($Experience\ level\ of\ \mu = 15\ years$) and two supervisors ($\mu = 4\ years$) at the production lines were interviewed to understand the detailed production process. These discussions were very useful in mapping out the flow process and pointing out where the wastes emerge. Further interviews with the head of quality ($\mu = 12\ years$) were needed to provide more details concerning types of waste, their classifications, and quantities. This step was important in understanding what wastes are manufacturable or non-manufacturable and what their categories are. In total, ($n = 4$) employees were interviewed in X Groupd during the study period.

Quantitatively, the daily production rate (Kg) and the daily amount of various waste types (Kg) for both long and short pasta over the last three months were collected. To help understand the effect of other variables, production parameters (Water ratio, flour ratio, dough water temperature, cylinder temperature, machine head temperature and pressure, head fan speed, right and left screws speed, dozer noise, boiler temperature, hanging stand speed, pre-drying temperatures, dryer temperatures, stabilizer temperature, cooler temperature, and moisture levels) were gathered as well. Table 2 demonstrates a simplification of the data gathered.

Table 1. A Summary of LSS Applications in the Food Manufacturing Industry

Study	Industry Segment	Problem Addressed	LSS Tools Used	Key Outcomes
[11]	Ready Meals	Food waste tracking	IoT-based system	Achieved a 60.7% reduction in waste over nine months, resulting in approximately £306,873 in cost savings.
[13]	Italian Food Manufacturers	Food waste reduction	Case studies, "food waste hierarchy"	Identified key strategies like structured surplus food control systems.
[27]	Food Manufacturing	Waste reduction	DMAIC approach	Effective evaluation and reduction of waste, with actionable suggestions for process improvement.
[29]	Juice & Beverage	Manufacturing waste & low process cycle efficiency	DMAIC, various Lean & Six Sigma tools	Improved process cycle efficiency from 15.28% to 34.05%, with an estimated annual savings of $2.13 million.
[30]	Confectionery	Overfilling and rework	LSS methodology	Significant cost savings through the elimination of variability and waste.
This Study	Pasta Production	High defect rates in long pasta production	DMAIC, SPC, Fishbone, Regression, DoE, Pugh Matrix	Reduced waste-to-production ratio from 19.0% (control) to as low as 10.0%, proving the effectiveness of standardized speed settings. Near ~82 k JOD/year (≈ $116 k/year) cost saving.

Table 2. The nature of data collected and its sources

Cat	Data Type	Unit	Description	Sources	Duration
Production	Daily Production Rates	Kg	Production rates for long and short pasta	Production logs Supervisor interviews	
Waste	Daily Waste Amounts		Amounts of waste in different categories (hanging stands, dough, the mill, re-opening packages, floor fallen)	Quality department reports Quality head interviews	
Production Parameters	Water Ratio	%	The proportion of water to flour in the dough	Production logs Supervisor interviews	
	Flour Ratio	%	The proportion of flour in the dough mixture		
	Dough Water Temperature	°C	The temperature of water used in the dough	Technical specifications Production logs	
	Cylinder Temperature	°C	Temperature of the cylinder during extrusion		
	Head Temperature	°C	Temperature at the extruder head		
	Head Pressure	Bar	Pressure at the extruder head		
	Head Fan Speed	RPM	Speed of the fan at the extruder head		
	Right Screwer Speed	RPM	Speed of the right screw extruder		
	Left Screwer Speed	RPM	Speed of the left screw extruder		
	Dozer Noise	dB	Noise level of the dozer during operation		
	Boiler Temperature	°C	Temperature of the boiler		
	Hanging Stands Speed	m/min	The speed at which hanging stands move		
	Pre-Drying Temperatures	°C	Temperatures in the pre-drying chambers		
	Dryer Temperatures	°C	Temperatures in the drying chambers		
	Stabilizer Temperature	°C	Temperature in the stabilizer unit		
	Cooler Temperature	°C	Temperature in the cooling chambers		
	Moisture	%	Moisture content of the finished product	Quality department reports Supervisor interviews	Aug-Oct 2024

3.2. Defining the Problem and Processes

First, it is important to understand the flow of the pasta (long and short) manufacturing process before proceeding to the problem. The process (Figure 1) begins with the receipt and storage of raw materials, which are sent to the intermediate storage silos. From there, it heads to the dough-mixing stage, a fundamental step for both kinds. This mixed dough is sent forward to the extruding stage, where the process of pushing pasta with molds is done to get the pasta in the desired shape as long or short cuts. The first important short/long differentiation takes place in this phase. After extrusion, the pasta is cut into the desired length. The short pasta then undergoes an additional shaking treatment, intended to refine its surface and clean it from possible loose elements that could influence the final product before pre-drying.

Following cutting, pasta undergoes pre-drying to remove initial moisture content. This is an important step in preventing the pasta from clumping together and also serves as preparation for the main drying. Waste at this stage may arise due to poor handling or defective equipment. The main drying assures that the pasta attains the stipulated level of moisture content for stability and shelf life. After drying, the pasta is cooled in the cooling stage, which stabilizes its structure and prepares it for storage. The cooled pasta is then moved to the storing phase, where it is kept until it undergoes final cutting and packaging.

After the flow process had been identified, the exact amount of manufacturable and non-manufacturable wastes of long and short pasta was estimated. This is part of problem identification. This is an estimation based on data for the last three months (August-October 2024). The nonmanufacturable (Dough wastes and fallen on the floor) and manufacturable (Clean and within the closed production system) wastes were calculated, and their percentages to production were then estimated.

Figure 2 shows the amount of food waste over the three months, and it provides a breakdown of the types of waste from long and short pasta production, including their categories (manufacturable and non-manufacturable waste). In August, manufacturable waste for long pasta was 18,844 kg against 4,444.5 kg for short pasta. This was aggravated in September, with long pasta manufacturable waste reaching 44,185 kg, while short pasta was 7,209.778 kg. It reduced slightly in October but remained substantially high, at 38,726.5 kgs against 7,036.2 kgs for short pasta. Initial indicators.

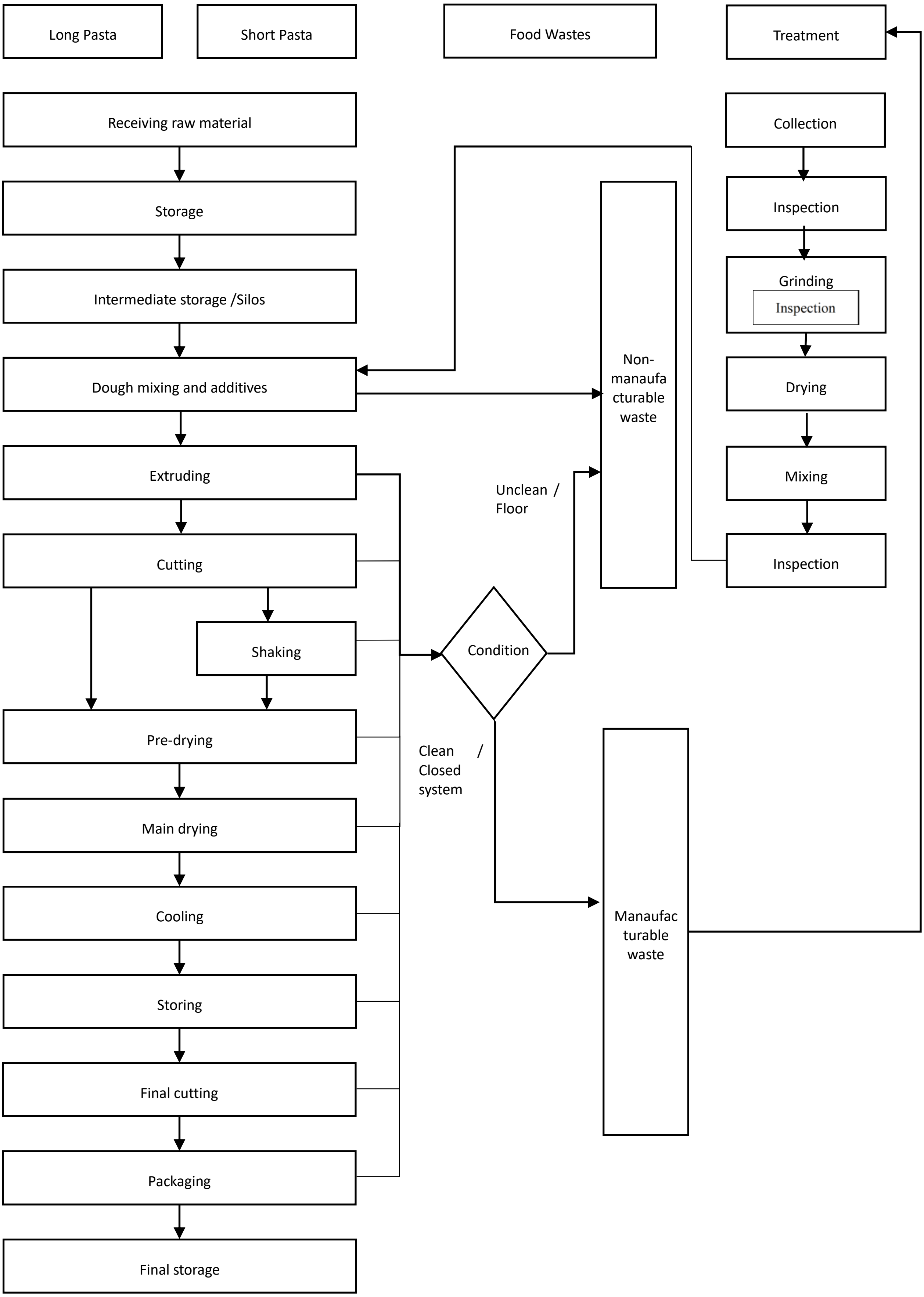

Figure 1. The flow chart of pasta production and the emergence of wastes

To validate the preceding results, the total amount of waste for the three months was added up, and the percentage for each of the four categories was calculated. The Pareto chart in Figure 3 shows that the sum of waste accounted for 130,584.098 kg (100%). The percentages of the non-manufacturable and manufacturable long pasta wastes were 4.875% and 77.923%, respectively. For short pasta, the non-manufacturable and manufacturable wastes were 2.888% and 14.313%, respectively. In general, the manufacturable amount of waste is higher than the non-manufacturable and most importantly is that the significant waste comes from the long pasta. Moreover, the Pareto (80-20) rule applies since nearly 80% of the waste comes from 20% of the types (Long manufacturable wastes). Consequently, efforts will be put towards reducing this category.

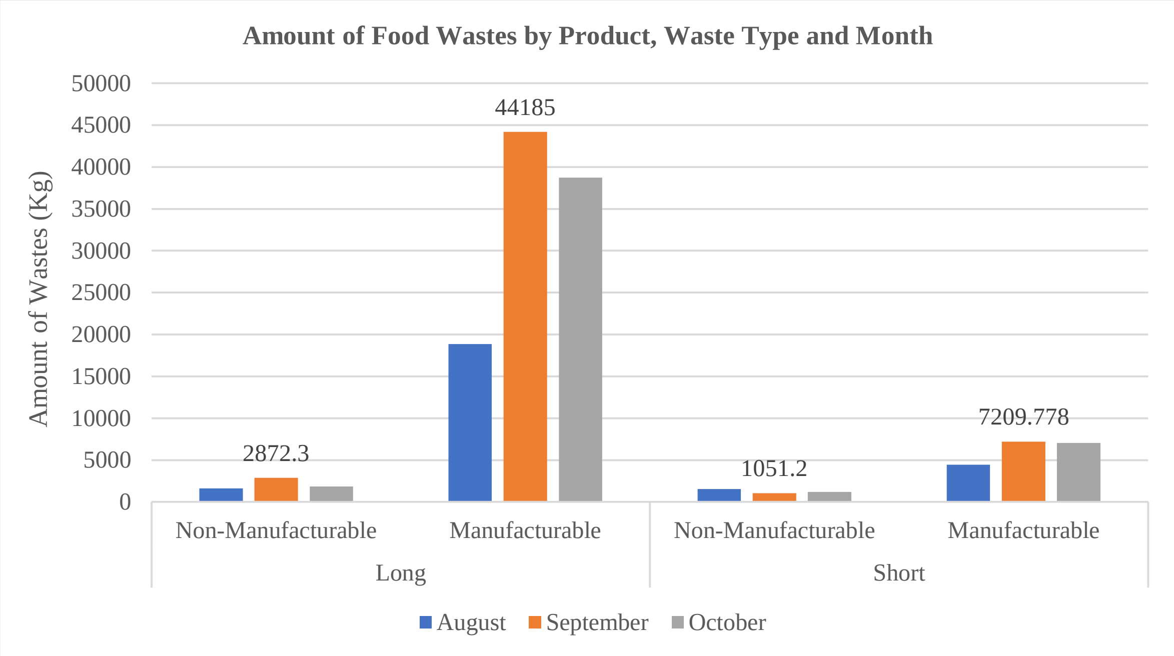

Figure 2. The amount of food waste by-product, waste category, and month

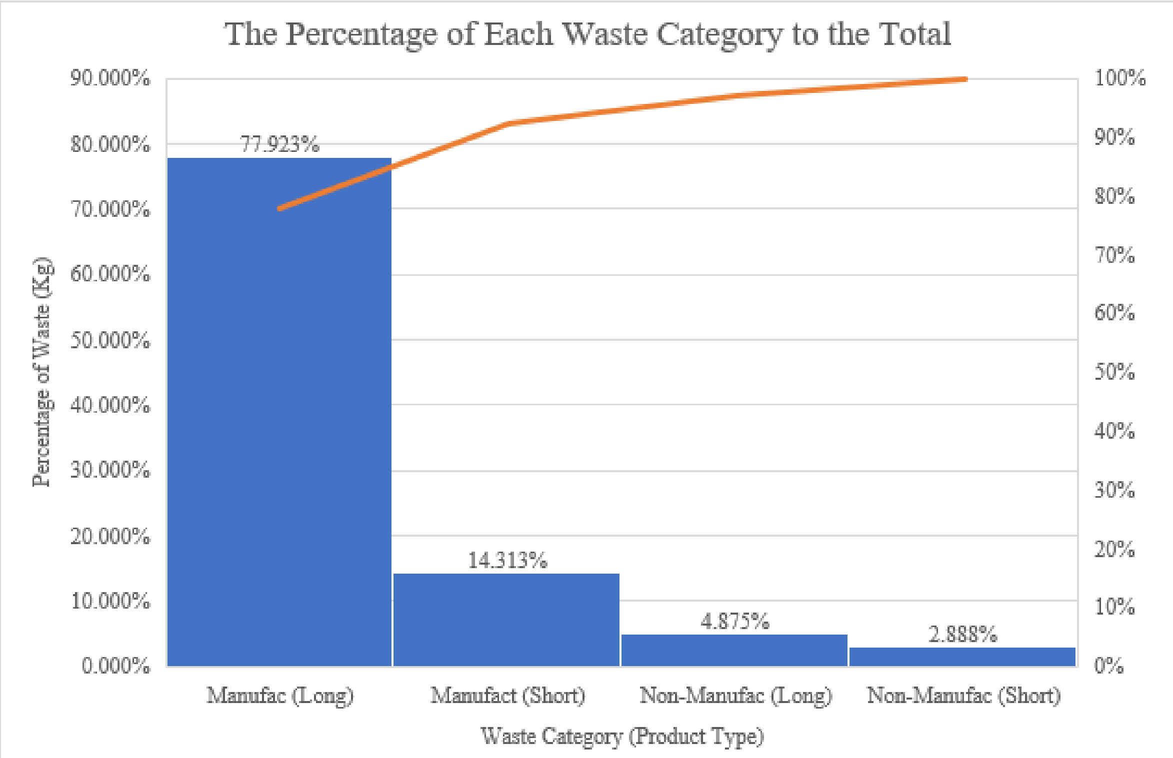

Figure 3. Pareto plot showing the percentages of each waste category to the total (August-October 2024)

3.3. The Methods of Analysis

Various quantitative analytical methods will be applied to the measured data to identify the main determinants of waste in the production of long pasta. SPC will be at the heart of the analysis, supplemented by various statistical tests (Regression and Root-Cause Analysis -RCA-).

Since the production is continuous over the three shifts and due to the fact that a significant amount of waste remains within the closed system, the amount of waste is weighted (in Kg) at the end of the day (n=1) and reported to the quality department the following morning, Individual–Moving Range (I/MR) control charts would be an ideal tool to assess process stability and find potential sources of waste [31]. The I/MR uses discrete data, and the MR component enables the tracking of small shifts or changes between consecutive days [32].

The multiple regression analysis would analyze the relationship between various production measures and the amount of waste. This technique can answer how different controlled variables (such as temperature, humidity, and other machine parameters) can affect the level of waste. It measures the strength of such associations and their overall impact on the model [33]. Moreover, the analysis phase will be supported by RCA in order to find the bottom line behind high rates of waste. Techniques that would be used in order to perform RCA include Fishbone Diagrams-Ishikawa and 5 Whys. These will help drill down on potential causes of waste at either machine defects, human error, or operational inefficiency.

4. Analysis, Results and Discussion

This section is organized to mirror the DMAIC sequence that governed our study. We first revisit the Define decisions to anchor the problem and critical-to-quality (CTQ) metric; we then discuss Measure (baseline performance and stability), Analyze (drivers and mechanisms), Improve (experimental validation and operational change), and Control (sustainment and monitoring

4.1. Descriptive Statistics for the Manufacturable Long Pasta Waste

The first subsection presents the descriptive statistics of long pasta's manufacturable waste. The focus will be on manufacturable waste collected during the three months of August, September, and October 2024. During these three months, X produced long pasta on 24, 21, and 25 production days, respectively. The analysis excludes weekly vacations, which typically occur on Fridays in Jordan, as well as other non-production days based on the scheduled plan.

The average daily manufacturable waste for long pasta production varied, with the mean values being 1,841.04 kg in August, 1,844.12 kg in September, and 2,354.90 kg in October. The standard deviation also increased from 397.59 kg in August to 380.26 kg in September and then to 692.48 kg in October. The last month has a higher level of quantity and variability in waste during October. Looking at the Boxplot in Figure 4, some days in the last two months have much higher or lower amounts of waste compared to the rest of the data points (outliers). This can be linked to other factors that led to an unexpected increase/ decrease in manufacturable waste on those days.

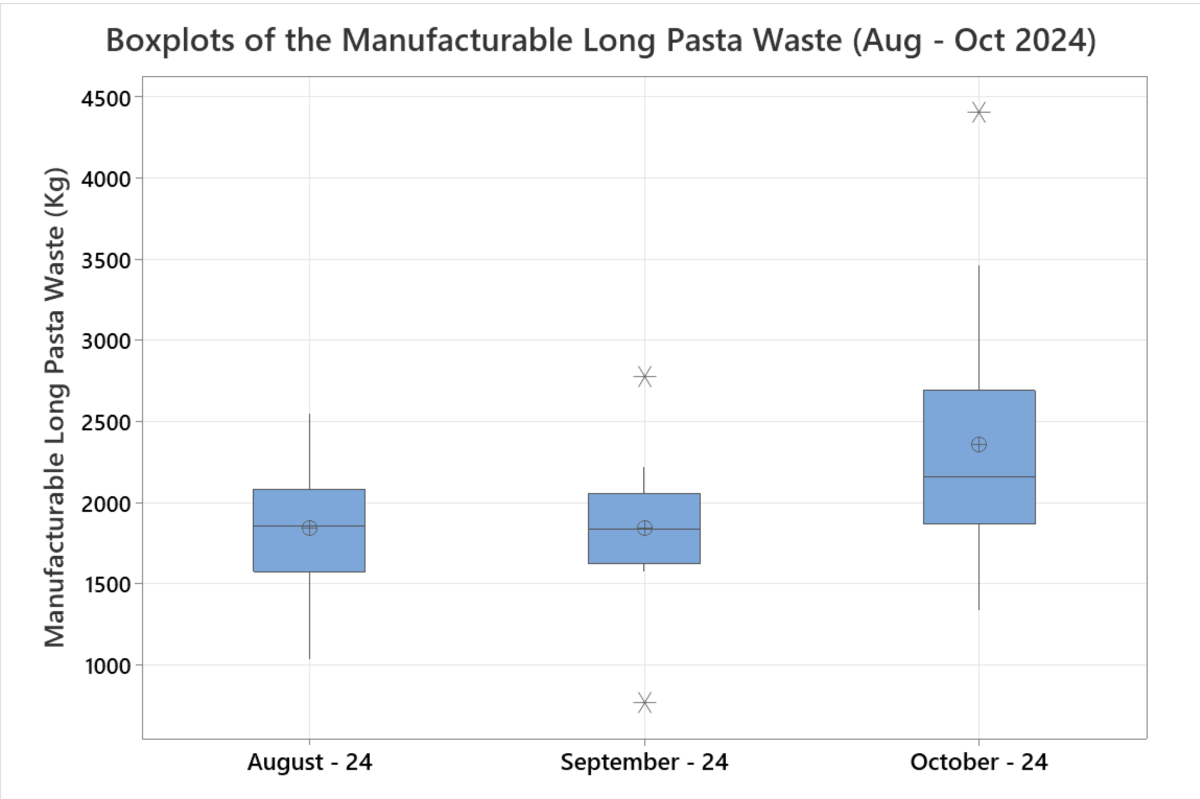

Figure 4. Boxplot showing the distribution of the daily amount of manufacturable long pasta waste during August-October 2024

To make the comparisons of manufacturable long pasta waste more realistic and accurate, we calculated the ratio of manufacturable long pasta waste to daily production for each day. Equation (1) was used in the calculation.

$$Ratio = \frac{Manufacturable\ Long\ Pasta\ Waste\ (Kg)}{Daily\ Long\ Pasta\ Production\ (Kg)} \quad (1)$$

Using the ratio will normalize the levels of waste with respect to the volume of pasta produced. The mean ratios for the three months were 0.1570 in August, 0.1719 in September, and 0.2122 in October, indicating an increasing trend in the waste-to-production ratio over the period. The new boxplot (Figure 5) provides a clearer view of how waste relates to the production volume. In general, there is a similarity between Figures 4 and 5 in terms of the increasing waste trend by month and the variability. However, the lower outlier in Figure 4 (for September) has disappeared, meaning that the production quantity was low on the same day. This is why analyzing the ratio would be more accurate and realistic in further analysis.

4.2. SPC and Further Analysis

After normalizing the data, the I-MR chart was selected for the entire dataset representing the three months. Normalization of data ensures that the comparison between different months is more accurate and consistent, as variations in the level of production will not be reflected in the analysis. This approach gives a comprehensive overview (macro) of the production process's stability and variability while still allowing us to delve into each month's micro-level data to identify specific trends and issues.

The I-MR chart (Figure 6) of the normalized data shows that the average ratio is 0.1812, which is high. This high average indicates that there is a problem resulting in a large amount of waste for this type. Several points are outside the control limits and are all above the Upper Control Limit (UCL). Assignable causes may be behind these deviations in ratios. From a micro perspective, October has a higher waste ratio compared to the previous two months. An ascending shift in the mean is clear and this aligns with the results of Figure 5.

The MR control chart also shows high variability in the ratio of waste to production. It indicates that some special causes are reasons for instability. The high average moving range (6.6%) and the out-of-control points (during September and October) reflect that these causes influence the process.

The out-of-control points on the I-MR chart, particularly the cluster of high waste ratios observed during October, are not merely random occurrences but are the result of assignable causes. Our subsequent root cause analysis, including the multi-level fishbone diagram, identified a critical link between these deviations and human-controlled machine parameters. As the regression analysis confirmed, hanging stand speed is the most statistically significant variable affecting the waste-to-production ratio. Interviews with production employees revealed a tendency to manually adjust this speed to increase output and finish work earlier, as later investigations reveal.

In the next step, part of the analysis phase of DMAIC, the RCA (Fishbone diagram) will be utilized to identify the main causes contributing to high waste-to-production ratios for long pasta production. The plot in Figure 7 was drawn based on the interviews with production and quality departments in X, and it graphically shows the main causes based on popular categories such as method, machine, material, manpower, management, and environment (Mother Nature).

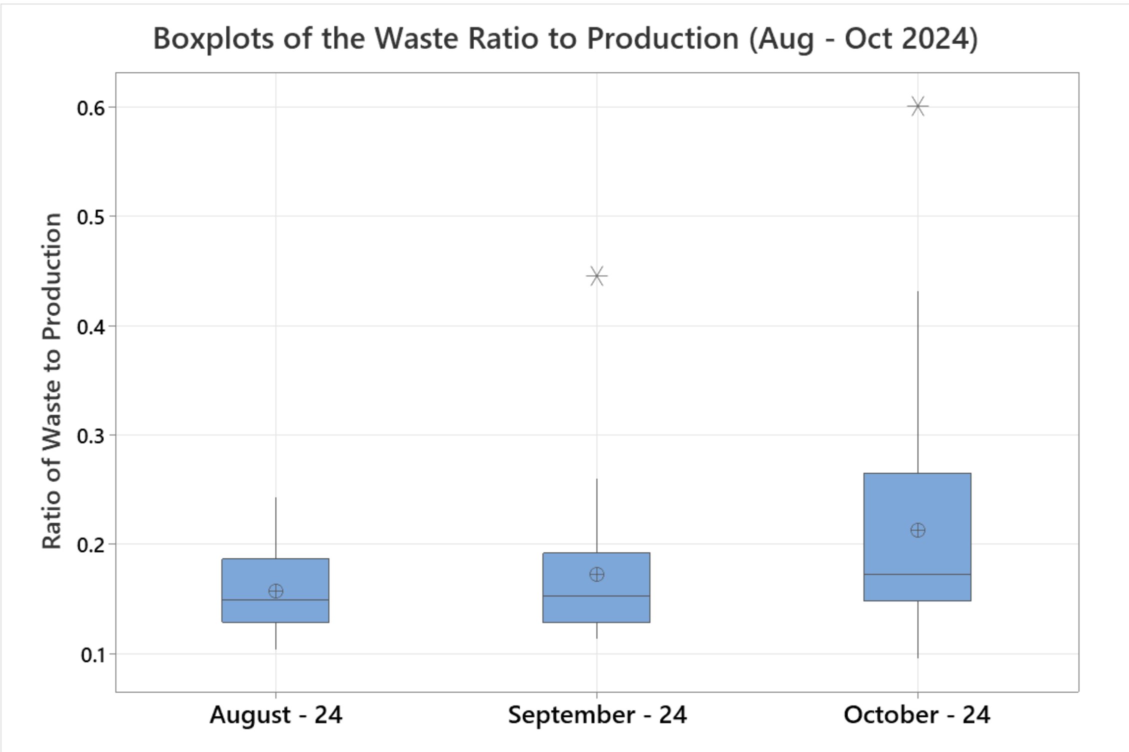

Figure 5. Boxplot showing the ratio of manufacturable long pasta waste to production during (August-October 2024)

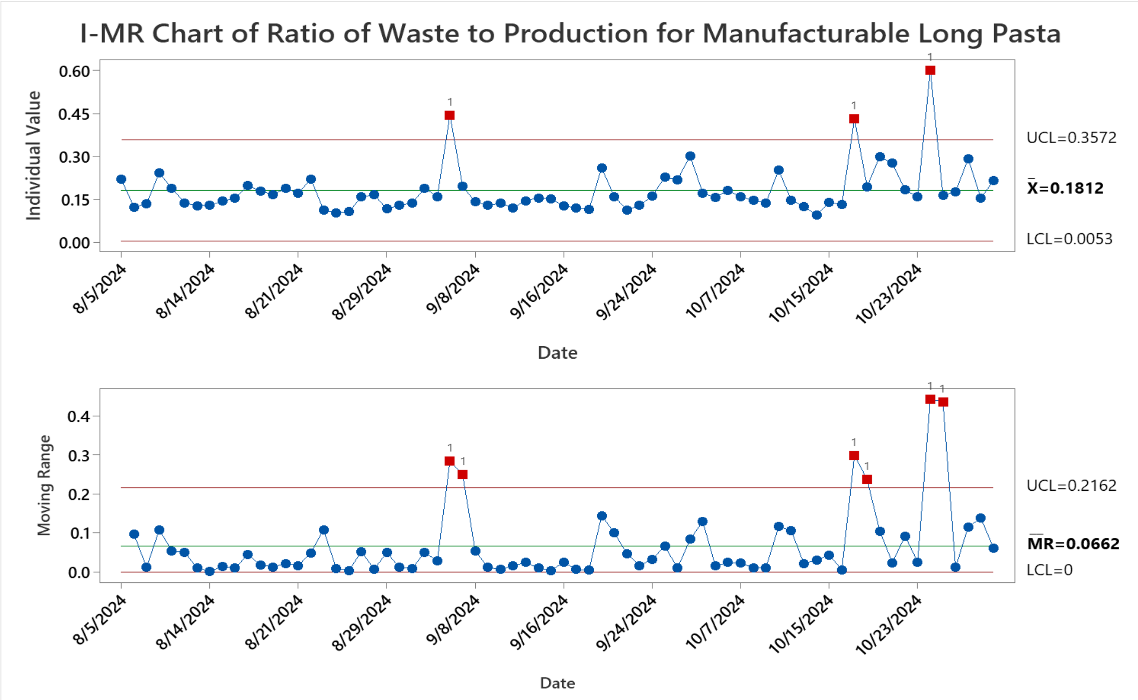

Figure 6. I-MR chart for the ratio of manufacturable long pasta waste to production during (August-October 2024)

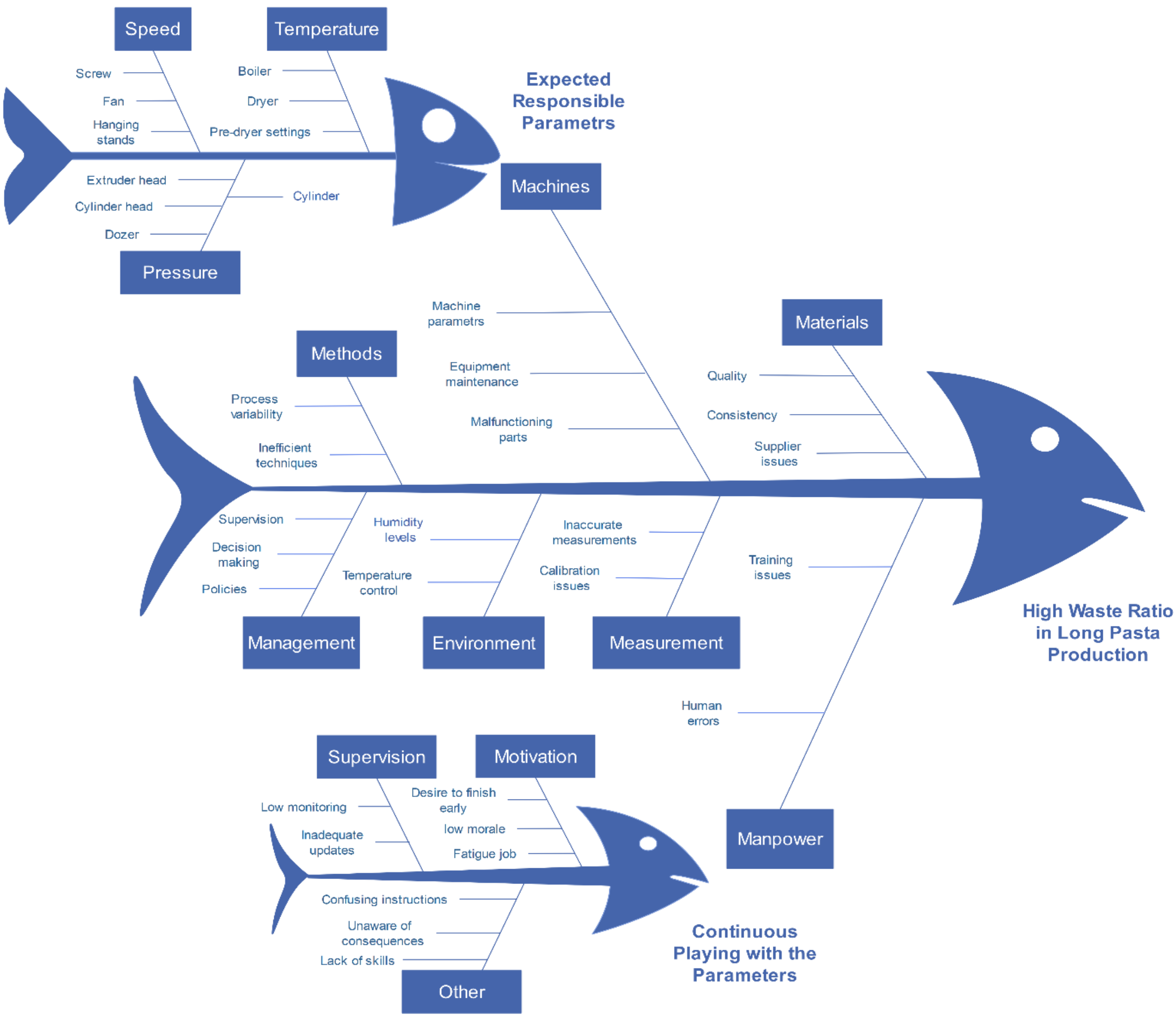

Figure 7. Fishbone diagram for the root causes of high waste ratio problem for long pasta

The multi-fishbone diagrams offer a comprehensive visual analysis of the high waste ratio problem in long pasta production (Big fish). The smaller fish are for machines and manpower. The machine fish identifies the main parameters that may cause the high waste and variability, which helps in solving the problem later on. The manpower fish digs in the reasons behind continuous playing with the parameters by the operators. Based on observations and interviews with quality department engineers, operators tend to alter the parameters for many reasons. For example, most production employees (not only in food industries) like to finish their work to leave early or start with the remaining tasks. The simplest way is to increase the speed of the machine by adjusting the parameters, such as the speed of the hanging stands. Low supervision and unawareness of the consequences increase the issue. To understand the correlations between the machine parameters and the high waste ratio, a regression analysis is computed. Data for different machine parameters were collected, and then the cleaning phase was initiated since the machine operators documented them during the three shifts. The cleaning phase included removing any empty rows for any machine parameters or the waste-production ratio to maintain accuracy. The outliers and normalization were tested, and any duplicates were removed. During the cleaning phase, (n=9) rows were removed due to lack of information/ missing on the machine parameters at these dates. Consequently, (n-61) samples were included in the regression analysis. In the following phase of cleaning, the parameters that have constant values during the period (August-October 2024) were excluded since the aim of the analysis is to reveal the effect of the variables that are causing the variability in food waste ratios. Examples of these variables are the head temperature (°C) and the speed of the head fan (RPM). After that, the data was ready to go through a regression test.

The multiple linear regression model was used to study the effect of the remaining four machine parameters (Head Pressure, Dozer Speed, Boiler Temperature, and Hanging Stands Speed) on the Waste Production Ratio (Respons). Having an $R^2 = 12.97\%$ means that the model seems to explain only a small portion of the variance in the dependent variable. The $R^2(pred) = 0.74\%$ means that this model is poor in terms of the forecast of new or future observations. Therefore, the numbers mean that while the machine parameters have some influence on waste, other factors likely play a more significant role.

The regression analysis (Table 3)shows that the Head Pressure (First predictor) has a coefficient of 0.00104, suggesting a minimal effect on waste and not statistically significant for the P-value of 0.804. The VIF is 1.00, suggesting no issues with regard to multicollinearity for this parameter. The Dozer Speed variable with a coefficient of 0.000262 indicates a very minor positive effect on the waste ratio. Its t-value of 1.67 and P-value of 0.100 indicate that it is close to statistical significance compared to other predictors.

Table 3. The output of the regression analysis

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-1.229	0.855	-1.44	0.156	-
Head Pressure	0.00104	0.00418	0.25	0.804	1.00
Dozer Speed	0.000262	0.000157	1.67	0.100	1.25
Boiler Temperature	0.00607	0.00722	0.84	0.404	1.11
Hanging Stands Speed	0.01234	0.00486	2.54	0.014*	1.17

* Significance at 5%
** Significance at 1%

The coefficient of Boiler Temperature is 0.00607, showing a positive but insignificant effect on waste with a P-value of 0.404. Lastly, Hanging Stands Speed gives a more remarkable coefficient of 0.01234, with a T-value of 2.54 and a P-value of 0.014. This is statistically significant at the 5% significance level but not 1% (more strict). In conclusion, between all machinery parameters, the speed of the handing stands showed a positive significant impact on waste levels. Its VIF is 1.17, which does not show multicollinearity. Based on the regression analysis, the regression equation can be written as shown in Equation (2).

$$\frac{\text{Waste}}{\text{Production}}\text{Ratio} = -1.229 + 0.00104\ \text{Head Pressure} + 0.000262\ \text{Dozer Speed} + 0.00607\ \text{Boiler Temperature} + 0.01234\ \text{Hanging Stands Speed} \quad (2)$$

To confirm the results, the Pareto chart (Figure 8) of the standardized effects for the Waste-Production Ratio illustrates the relative importance of each machine parameter to the production of waste. From the chart, it is obvious that the Hanging Stands Speed (D) is the largest effector in this analysis, exceeding the threshold value (represented by a red dotted line) of 2.003, which is the critical value for a statistically significant result at $\alpha = 5\%$. This means that variations in the speed of hanging stands are the most critical factor in changing the waste-production ratio and on which control and improvement measures should be therefore concentrated. On the other hand, Dozer Speed (B) also exhibits an appreciable effect but does not reach the significance threshold, while Boiler Temperature (C) and Head Pressure (A) have less contribution, their effects falling considerably below the level of significance, showing a very weak influence of these variables in regard to the waste-production ratio in the model setup.

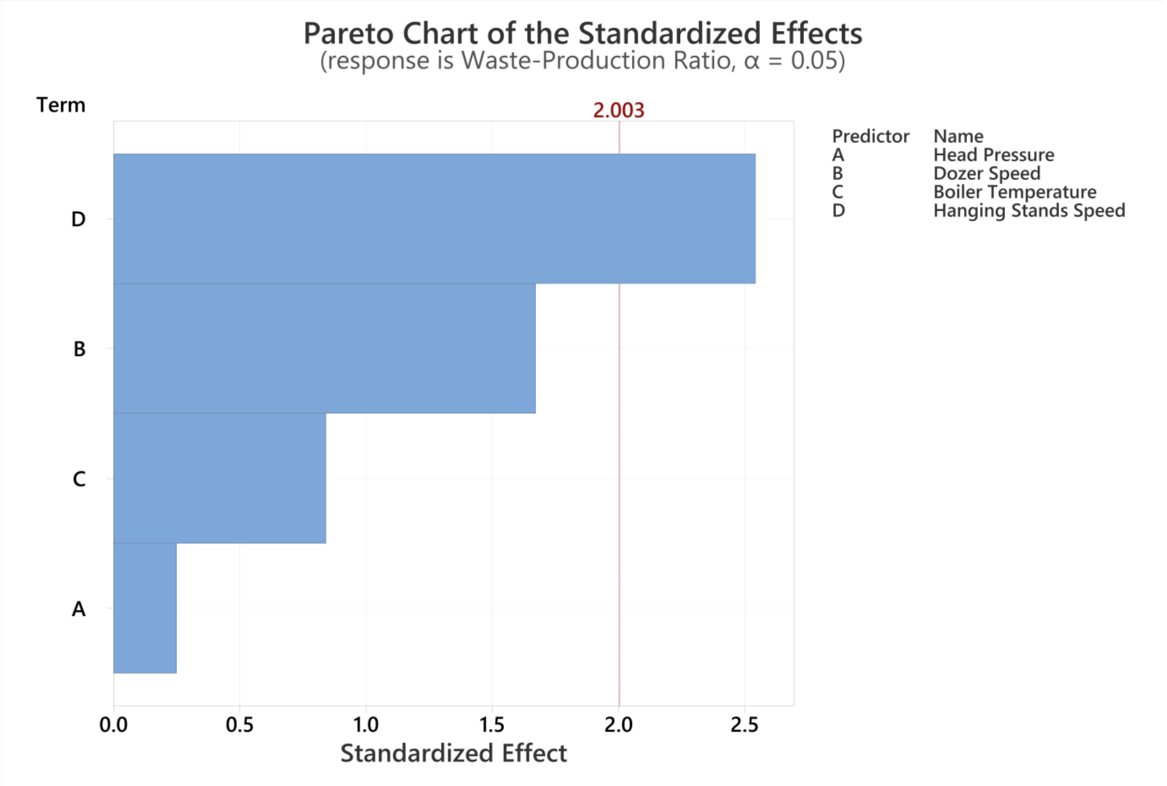

Figure 8. Pareto chart of the standardized effects showing the effect of the four machine parameters on the Waste/Production ratio for long pasta

Returning to machine parameters data that each production shift supervisor documents, the shifts with higher average hanging stand speeds usually have higher waste quantities despite having larger production rates. This tends to suggest that at higher speeds-while the machinery is indeed capable, the quality of the handling becomes so bad that the amount of waste generated increases and can even completely offset the economic advantage of higher throughput. Additional wear on machinery could also raise maintenance needs and costs, further affecting operational efficiency.

To ensure the validity and reliability of the multiple linear regression model, the key assumptions of the analysis were carefully checked. These assumptions include:

- The relationship between the predictors and the response variable is linear.
- The residuals (errors) are independent of each other.
- The variance of the residuals is constant across all levels of the predictors.
- The residuals are normally distributed.

A visual inspection of the residual plots (Residuals versus Fitted Values) confirmed that there was no discernible pattern, indicating that the assumptions of linearity and homoscedasticity were reasonably met. Furthermore, a normal probability plot of the residuals showed that the data points fell along a straight line, confirming the assumption of normality. These diagnostic plots are included in Appendix A, and an example is also shown within the analysis summary.

4.3. Improve and Control

During the Improve phase of the DMAIC process and following several brainstorming sessions by various stakeholders (including the quality department), creative solutions for production process optimization were brought to the floor. Five practical and innovative solutions are proposed to optimize the pasta production process. The first is to implement an automated system that records the speeds of different machine parameters, including hanging stands, based on real-time conditions instead of the manual data filling to track better and analyze the problem. The second is to install more precise speed control systems for the machines, which are adjustable on strict conditions and require multiple authentications (Such as operator and supervisor). The third was to standardize speed settings based on different production loads and types of pasta and according to machine manuals. A fourth solution was to introduce a closed-loop system to recycle waste produced during the manufacturing process. The last solution calls for introducing Artificial Intelligence (AI), machine vision, and the Internet of Things (IoT) as part of Industry 4.0 principles to track and monitor the machine readings and the waste quantities. However, the stakeholders agreed that the last solutions may need time and a strong technological infrastructure in addition to their high costs. To evaluate the solutions based on criteria like feasibility, cost, impact on production, and ease of implementation, a Pugh Matrix was used as shown in Table 4.

Pugh Matrix ranks each solution against the baseline (current method), showing the relative strengths and weaknesses between the solutions. Based on these results, combined with stakeholders' preferences, the best solution chosen is to standardize speed settings since it held the highest ranking of 1. It facilitates a reduction in waste, adding its value in terms of cost-effectiveness, while there is no need for enormous investment in its use or alteration to be affected by established infrastructures.

Automated Data Recording and Precise Speed Controls take the second position since they are equally viable options from the base case. Closed-loop recycling comes fourth and has various challenges, especially in ease of implementation, cost-effectiveness, and requirements of employee training. However, it scores high in effectiveness in waste reduction. The least favorable option is AI/IoT Tracking & Control, ranking fifth. Despite its potential benefits in reducing waste and improving scalability, its high costs, significant training requirements, and the need for a technological infrastructure pose challenges.

As part of the Improve phase in the DMAIC process, the Design of Experiments (DoE) methodology was utilized to evaluate the effectiveness of the standardized speed settings in the pasta production environment. The first step involves the implementation of the solutions that were selected based on their strong performance in the Pugh Matrix. Second, the same experimental conditions studied in regression analysis were considered in DoE. Third, the DoE has considered four groups as follows:

1. Control Group: Production runs using the previous, non-standardized speed settings.
2. Experimental Group 1: Production runs using the standardized speed settings at low production loads.
3. Experimental Group 2: Production runs using the standardized speed settings at medium production loads.
4. Experimental Group 3: Production runs using the standardized speed settings at high production loads.

Data was gathered over several weeks to ensure comprehensive and accurate information. Supervisors ensured the standardization of key machine parameters, such as the hanging stand speed, during each shift. Additionally, reports from the quality control team were reviewed to classify waste types and measure defect rates. Table 5 shows the results of the DoE analysis.

To validate the significance of the observed reductions in the waste-to-production ratio, a one-way ANOVA (Analysis of Variance) was performed to statistically compare the means of the four groups (Control, Experimental Group 1, Experimental Group 2, and Experimental Group 3). The ANOVA test (Table 6) revealed a statistically significant difference among the group means, with a p-value less than 0.05. This result allows us to reject the null hypothesis that there is no difference in the waste ratios among the groups.

Table 4. The Pugh matrix comparing the five solutions for the high waste problem

Criteria	Alternatives							
	Baseline (Current Method)	**Automated Data Recording**	**Precise Speed Controls**	**Standardized Speed Settings**	**Closed-Loop Recycling**	**AI/IoT Tracking & Control**	**Totals**	**Rank**
Ease of Implementation	+	0	0	+	−	−	-1	7
Cost (Monetary & Nonmonetary)	-	0	0	+	−	−	-1	7
Effectiveness in Reducing Waste	-	+	+	0	+	+	4	1
Infrastructure Readiness	0	+	+	+	+	−	3	3
Employee Training Requirments	0	0	0	0	−	−	-2	9
Scalability	-	+	+	+	0	0	3	2
Totals		3	3	4	-1	-3		
Rank		**2**	**2**	**1**	**4**	**5**		

Table 5. Production and waste data summary after performing the DoE*

Group	Production (kg/day)	Manufacturable Waste (kg/day)	Non-Manufacturable Waste (kg/day)	Total Waste (kg/day)	Waste to Production Ratio (%)
Control Group	10,000	1,300	600	1,900	19.0
Experimental Group 1	7,000	500	200	700	10.0
Experimental Group 2	10,000	1,000	450	1,450	14.5
Experimental Group 3	13,000	1,200	500	1,700	13.1

* "Low/Medium/High" loads correspond to production-volume tiers derived from the Q1/median/Q3 of the plant's 2024 daily-production distribution; the listed 7,000 / 10,000 / 13,000 kg·day^{-1} are representative runs for each tier. Groups 1–3 use the standardized speed policy applicable to their tier; the Control Group uses pre-study (non-standardized) speeds

Table 6. Results of the One-Way ANOVA for DoE Groups

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-value	p-value
Group (Between Groups)	0.005	3	0.0017	10.38	<0.001
Error (Within Groups)	0.003	24	0.0001		
Total	0.008	27			

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The statistical significance of the findings confirms that the reduction in waste-to-production ratio is a direct and measurable effect of implementing the standardized speed settings, and not merely a result of random process variation. This statistical inference strengthens the conclusion that the standardized speed settings approach is a highly effective and evidence-based solution for reducing waste in the long pasta production process.

The DoE offers clear results on how tuning machine parameters standardization can drastically reduce waste. The first group significantly reduced both manufacturable and non-manufacturable scrap and achieved a total waste of 700 kg/day from a production of 7,000 kg/day. The Waste-to-Production Ratio dropped to 10.0%, which is 47.4% lower than that of the Control Group, but again, at the expense of reduced production rate. The second group produced the same amount as the Control Group but reduced total waste to 1,450 kg/day. This gives a Waste-to-Production Ratio of 14.5%, which is a 23.7% reduction in waste percentage. The third group, at high production loads, has increased production to 13,000 kg/day and also the Waste to Production Ratio at 13.1%. However, this remains below the control group values, which proves the effectiveness of standardization in reducing the problem. The bubble plot in Figure 9 summarizes the DoE output (Also, see Appendix C).

In the last phase (Control), a monitoring plan is suggested to ensure the long-term success and sustainability of the newly implemented standardized speed settings in pasta production. The strategy will involve constant performance appraisals on the setting performance to meet consistently targeted efficiencies or levels of expected reduction of waste products. The plan includes conducting scheduled weekly and monthly reviews to assess the production data and waste metrics. Advanced monitoring software may also be leveraged whereby real-time data on key machine parameters such as speed, pressure and temperature are continuously tracked. A feedback mechanism is to be instituted through production staff and supervisors. Finally, continuous training programs are highly recommended in order to update the production team with the best practices and operational procedures concerning the new settings.

4.4. Economic Impact Analysis

A critical component of any Lean Six Sigma project is demonstrating its financial viability. This section provides a simple economic impact analysis to quantify the value of the waste reduction achieved through the standardized speed settings. The analysis is based on a conservative estimation that the manufacturable waste, which constitutes the majority of the total waste (77.923%), can be recycled and reused, hence presenting a significant opportunity for cost savings. This percentage was approved by the production manager, who mentioned that the vast majority of waste is being reused by spreading it (in studied quantities) on future mixes.

According to [34], the average market price of Al-Ghazal spaghetti in Jordan is JOD 0.35 for 300g. The estimated price of the 1Kg is JOD 1.17. However, the actual price is expected to be lower by 10% (Profit margin) based on [35] report. This results in a cost of nearly JOD 1 for each 1 Kg. While manufacturable waste can be reused, the reduction of this waste still represents a substantial saving in labor, energy, and raw materials, and decreases the burden on the quality team. Moreover, it is an indirect financial gain from reducing the burden on the quality department, who may be forced to work more than a single shift and adding to the firm's operational flexibility. The non-manufacturable waste can be sold to other industries, hence another financial opportunity. The economic analysis focuses on the tangible savings from reducing the quantity of total waste. Following the previous assumptions, Table 7 demonstrates the cost savings from the improvements.

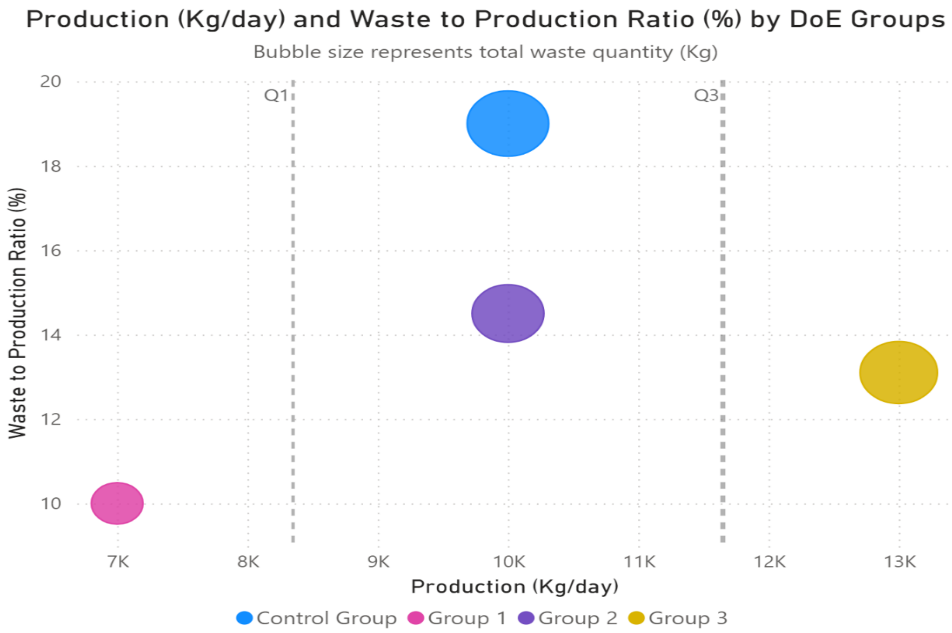

Figure 9. Production and waste-to-production ratio by DoE groups

* Q1 and Q3 are calculated based on historical production data for the year 2024, which helps to expect the reduced waste quantity through standardization

Table 7. Economic Impact of Waste Reduction (JOD)

Group	Total Waste (Kg/Day)	Scrap Waste Quantity (Kg)	Daily Savings (JOD)	Annual Savings (JOD)
Control Group	1,900	418	418	108,680
Exp. Group 1	700	154	154	40,040
Exp. Group 2	1,450	319	319	82,940
Exp. Group 3	1,700	374	374	97,240
Average	1,438	316	316	82,225

Using a 22% scrap fraction, the scrap waste quantity for each group is simply 0.22× its total waste (kg/day). With a unit cost of 1 JOD per kg, the daily savings (JOD) numerically equals the scrap kg; annual savings (JOD) = daily savings × 260 operating days.

The average total waste across all groups is 1,438 kg/day, which translates to an average scrap waste quantity of 316.25 kg/day. This results in an average daily saving of JOD 316, and an average annual saving of JOD 82,225. Under these assumptions, moving from the control practice to the standardized policy yields, on average, ~316 kg/day of scrap avoided, translating to ~316 JOD/day (≈ $446/day) and ~82 k JOD/year (≈ $116 k/year) in direct cost avoidance, before any secondary benefits. Beyond direct material loss, food waste imposes hidden operational costs that are not captured in the base savings (1 $JOD \cdot kg^{-1}$). Each waste event typically triggers collection/segregation, machine and floor sanitation (CIP/foam/washdown), purging/restart losses, temporary line speed reductions, and internal logistics (bins, lifts, transport to waste points). These activities consume labor time, utilities (water, steam, electricity, compressed air), cleaning chemicals and PPE, and disposal/wastewater capacity, while also degrading OEE (availability and performance), pulling maintenance effort, and occasionally prompting quality investigations/rework.

The outcomes of this study resonate with and contribute to the existing body of literature on Lean Six Sigma applications in the food industry. Similar to the study by [30], which used LSS to reduce overfilling and rework in a confectionery and achieved significant cost savings, our project demonstrated a notable reduction in waste and operational variability. Our economic analysis, which projects substantial annual savings for X Group, is consistent with the findings of [29], who reported significant economic benefits and improved process efficiency in a food processing industry using a similar methodology.

Additionally, this study's application of the DMAIC parallels [36] work, which used the same framework to address variability in ghee production (Food) within a Jordan Vegetable Oil Industry (JVOI) company. Both studies demonstrate the effectiveness of DMAIC in a specific industrial context to solve quality and productivity problems by identifying root causes and proposing data-driven solutions. The results also back up the wider research that says LSS tools are good for fighting food waste all through the supply chain. While our study confirms these general findings, it stands out by giving a super detailed, step-by-step look at how to use a multi-tool LSS plan for one specific item — long pasta — filling a known gap in the research and giving a replicable, data-driven example for others in the industry. It's truly a pivotal contribution. We've managed to extirpate some of the production waste that's been a plague in this sector.

5. Conclusion

This work aims to reduce waste within the long pasta production process in X by applying LSS methodologies. The methods involved problem identification and analysis tools such as the SPC, fishbone diagrams, regression analysis, DoE and Pugh matrix for alternative selection. The study suggested and implemented the standardized speed settings approach, which was chosen as a main strategy for improvement.

Through controlled experiments and statistical evaluation, significant improvements in waste reduction were determined from the analyses. For the control group, the waste-to-production ratio was 19.0%, while for Experimental Group 1, it came down to 10.0%, Experimental Group 2 managed to bring it down to 14.5%, and Experimental Group 3 brought it further down to 13.1%. The results indicate that standardized speed settings are capable of reducing the amount of waste while maintaining good production rates.

The findings of this study, while derived from the specific context of a long pasta production facility in Jordan, possess a high degree of transferability and contextual relevance. The Lean Six Sigma DMAIC methodology employed is a universally applicable framework for systematic process improvement and waste reduction. The core insights—that a significant portion of manufacturing waste can be reduced by controlling key machine parameters and addressing human factors—are relevant not only to other food processing plants but also to a wide range of manufacturing industries facing similar challenges of operational variability.

To ensure the long-term sustainability and continued relevance of the improvements achieved, several follow-up actions and future outcomes are highly recommended. First, the company is strongly encouraged to implement the second and third viable alternatives identified in the Pugh matrix: Automated Data Recording and Precise Speed Controls. Second, continuous training programs are essential to educate employees on the new principles and operational procedures, which foster a culture of cleaner production and reduce human error. Finally, for future research, X Group should consider integrating advanced predictive analytics and machine learning algorithms further to optimize the standardized speed settings in real time, mitigating potential sources of waste before they occur.

Among the recommendations is incorporating advanced predictive analytics and machine learning algorithms into the refinement of standardized speed settings. Automated Data Recording and Precise Speed Controls (Second and third alternatives) are highly recommended to the company. Future research can extend to study the effects of these solutions. However, the generalizability of the findings may be limited to operational contexts that may be different from other geographical locations. Also, relying on manual readings for machine adjustments might introduce human errors, influencing the accuracy and consistency of the results. Finally, we could not implement the value stream mapping due to insufficient granularity: missing step-level cycle time/ lead time distributions, work in process by buffer/supermarket, setup time/changeovers, overall equipment effectiveness by process, and the information-flow layer (pacemaker, pitch/takt, pull signals).

Data Availability

Data is available upon reasonable request. Screenshots were attached with the submission as evidence and to support open data initiatives.

Conflict of Interest

This work has no conflict of interest of any type.

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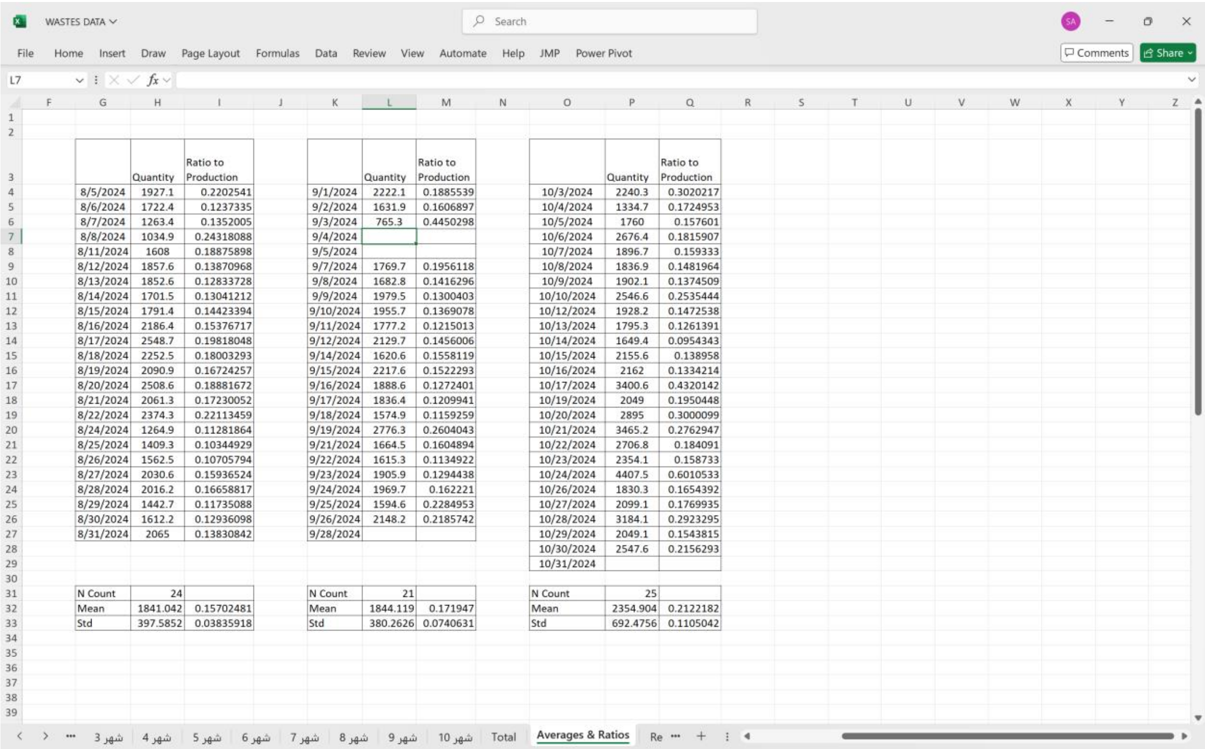
Appendix A – Excel Analysis (Regression, Data Cleaning, Ratios)



	Quantity	Ratio to Production
8/5/2024	1927.1	0.2202541
8/6/2024	1722.4	0.1237335
8/7/2024	1263.4	0.1352005
8/8/2024	1034.9	0.24318088
8/11/2024	1608	0.18875898
8/12/2024	1857.6	0.13870968
8/13/2024	1852.6	0.12833728
8/14/2024	1701.5	0.13041212
8/15/2024	1791.4	0.14423394
8/16/2024	2186.4	0.15376717
8/17/2024	2548.7	0.19818048
8/18/2024	2252.5	0.18003293
8/19/2024	2090.9	0.16724257
8/20/2024	2508.6	0.18881672
8/21/2024	2061.3	0.17230052
8/22/2024	2374.3	0.22113459
8/24/2024	1264.9	0.11281864
8/25/2024	1409.3	0.10344929
8/26/2024	1562.5	0.10705794
8/27/2024	2030.6	0.15936524
8/28/2024	2016.2	0.16658817
8/29/2024	1442.7	0.11735088
8/30/2024	1612.2	0.12936098
8/31/2024	2065	0.13830842

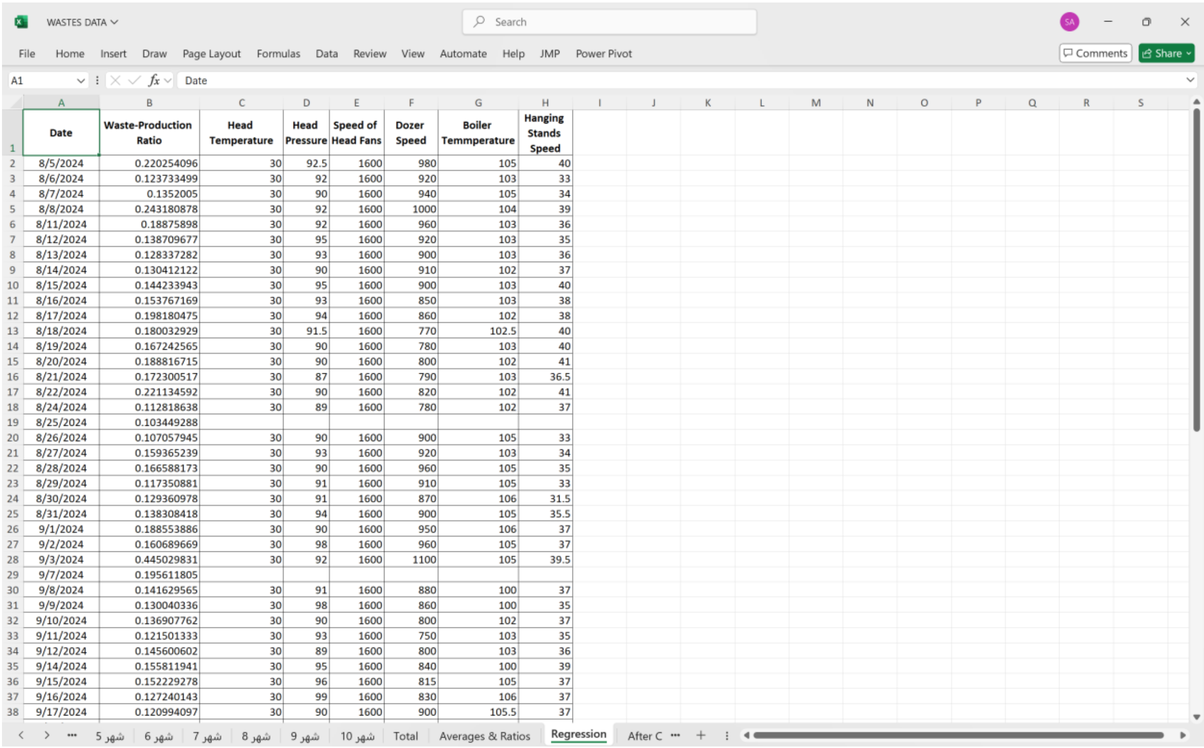
N Count	24	
Mean	1841.042	0.15702481
Std	397.5852	0.03835918

	Quantity	Ratio to Production
9/1/2024	2222.1	0.1885539
9/2/2024	1631.9	0.1606897
9/3/2024	765.3	0.4450298
9/4/2024		
9/5/2024		
9/7/2024	1769.7	0.1956118
9/8/2024	1682.8	0.1416296
9/9/2024	1979.5	0.1300403
9/10/2024	1955.7	0.1369078
9/11/2024	1777.2	0.1215013
9/12/2024	2129.7	0.1456006
9/14/2024	1620.6	0.1558119
9/15/2024	2217.6	0.1522293
9/16/2024	1888.6	0.1272401
9/17/2024	1836.4	0.1209941
9/18/2024	1574.9	0.1159259
9/19/2024	2776.3	0.2604043
9/21/2024	1664.5	0.1604894
9/22/2024	1615.3	0.1134922
9/23/2024	1905.9	0.1294438
9/24/2024	1969.7	0.162221
9/25/2024	1594.6	0.2284953
9/26/2024	2148.2	0.2185742
9/28/2024		

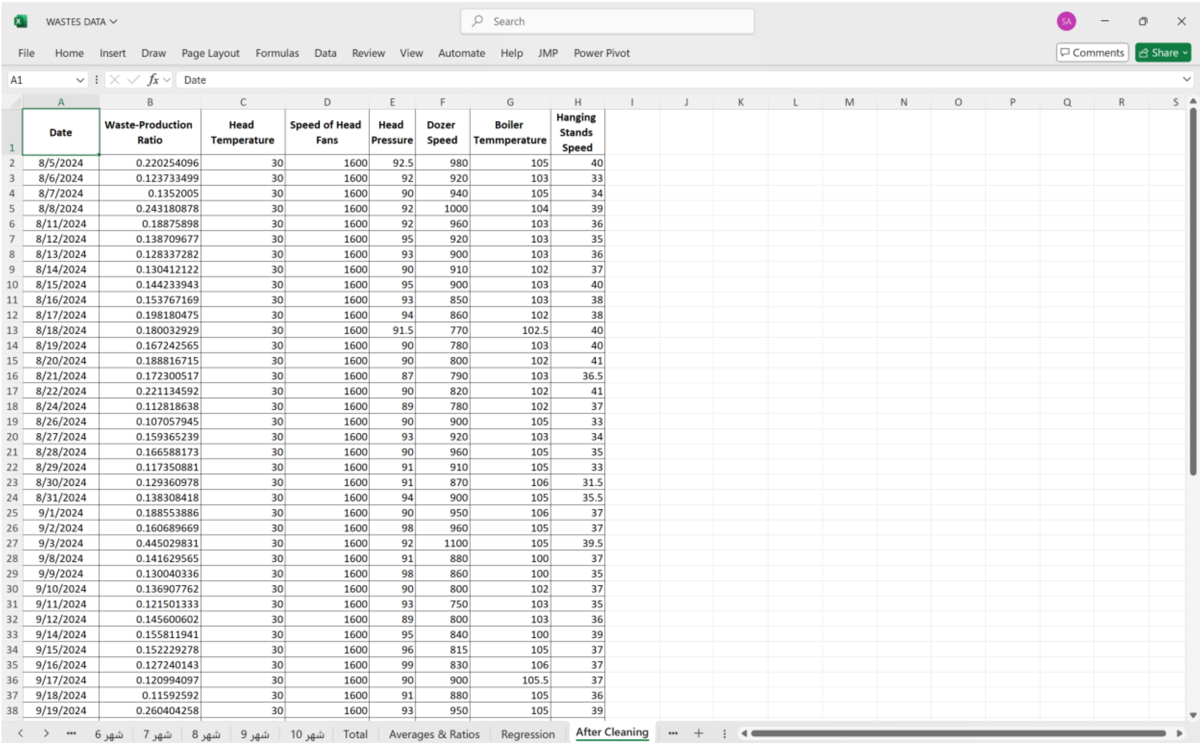
N Count	21	
Mean	1844.119	0.171947
Std	380.2626	0.0740631

	Quantity	Ratio to Production
10/3/2024	2240.3	0.3020217
10/4/2024	1334.7	0.1724953
10/5/2024	1760	0.157601
10/6/2024	2676.4	0.1815907
10/7/2024	1896.7	0.159333
10/8/2024	1836.9	0.1481964
10/9/2024	1902.1	0.1374509
10/10/2024	2546.6	0.2535444
10/12/2024	1928.2	0.1472538
10/13/2024	1795.3	0.1261391
10/14/2024	1649.4	0.0954343
10/15/2024	2155.6	0.138958
10/16/2024	2162	0.1334214
10/17/2024	3400.6	0.4320142
10/19/2024	2049	0.1950448
10/20/2024	2895	0.3000099
10/21/2024	3465.2	0.2762947
10/22/2024	2706.8	0.184091
10/23/2024	2354.1	0.158733
10/24/2024	4407.5	0.6010533
10/26/2024	1830.3	0.1654392
10/27/2024	2099.1	0.1769935
10/28/2024	3184.1	0.2923295
10/29/2024	2049.1	0.1543815
10/30/2024	2547.6	0.2156293
10/31/2024		

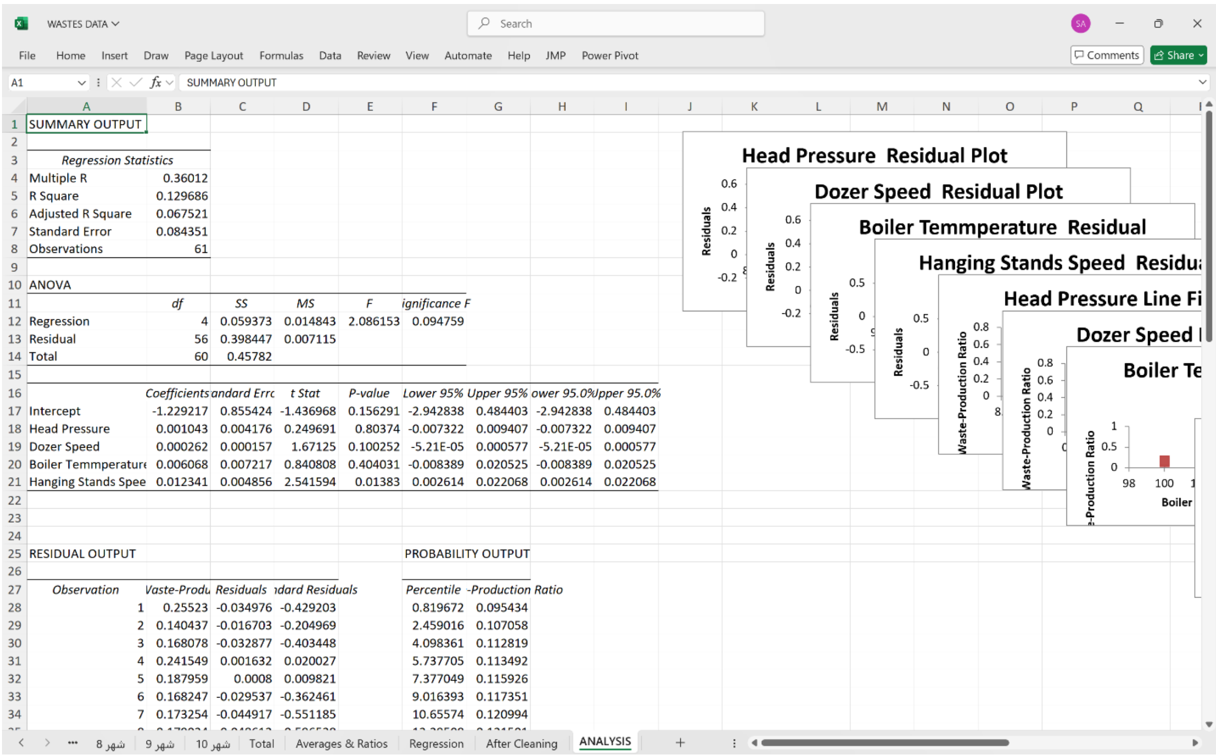
N Count	25	
Mean	2354.904	0.2122182
Std	692.4756	0.1105042



Date	Waste-Production Ratio	Head Temperature	Head Pressure	Speed of Head Fans	Dozer Speed	Boiler Temmperature	Hanging Stands Speed
8/5/2024	0.220254096	30	92.5	1600	980	105	40
8/6/2024	0.123733499	30	92	1600	920	103	33
8/7/2024	0.1352005	30	90	1600	940	105	34
8/8/2024	0.243180878	30	92	1600	1000	104	39
8/11/2024	0.18875898	30	92	1600	960	103	36
8/12/2024	0.138709677	30	95	1600	920	103	35
8/13/2024	0.128337282	30	93	1600	900	103	36
8/14/2024	0.130412122	30	90	1600	910	102	37
8/15/2024	0.144233943	30	95	1600	900	103	40
8/16/2024	0.153767169	30	93	1600	850	103	38
8/17/2024	0.198180475	30	94	1600	860	102	38
8/18/2024	0.180032929	30	91.5	1600	770	102.5	40
8/19/2024	0.167242565	30	90	1600	780	103	40
8/20/2024	0.188816715	30	90	1600	800	102	41
8/21/2024	0.172300517	30	87	1600	790	103	36.5
8/22/2024	0.221134592	30	90	1600	820	102	41
8/24/2024	0.112818638	30	89	1600	780	102	37
8/25/2024	0.103449288						
8/26/2024	0.107057945	30	90	1600	900	105	33
8/27/2024	0.159365239	30	93	1600	920	103	34
8/28/2024	0.166588173	30	90	1600	960	105	35
8/29/2024	0.117350881	30	91	1600	910	105	33
8/30/2024	0.129360978	30	91	1600	870	106	31.5
8/31/2024	0.138308418	30	94	1600	900	105	35.5
9/1/2024	0.188553886	30	90	1600	950	106	37
9/2/2024	0.160689669	30	98	1600	960	105	37
9/3/2024	0.445029831	30	92	1600	1100	105	39.5
9/7/2024	0.195611805						
9/8/2024	0.141629565	30	91	1600	880	100	37
9/9/2024	0.130040336	30	98	1600	860	100	35
9/10/2024	0.136907762	30	90	1600	800	102	37
9/11/2024	0.121501333	30	93	1600	750	103	35
9/12/2024	0.145600602	30	89	1600	800	103	36
9/14/2024	0.155811941	30	95	1600	840	100	39
9/15/2024	0.152229278	30	96	1600	815	105	37
9/16/2024	0.127240143	30	99	1600	830	106	37
9/17/2024	0.120994097	30	90	1600	900	105.5	37



Date	Waste-Production Ratio	Head Temperature	Speed of Head Fans	Head Pressure	Dozer Speed	Boiler Temmperature	Hanging Stands Speed
8/5/2024	0.220254096	30	1600	92.5	980	105	40
8/6/2024	0.123733499	30	1600	92	920	103	33
8/7/2024	0.1352005	30	1600	90	940	105	34
8/8/2024	0.243180878	30	1600	92	1000	104	39
8/11/2024	0.18875898	30	1600	92	960	103	36
8/12/2024	0.138709677	30	1600	95	920	103	35
8/13/2024	0.128337282	30	1600	93	900	103	36
8/14/2024	0.130412122	30	1600	90	910	102	37
8/15/2024	0.144233943	30	1600	95	900	103	40
8/16/2024	0.153767169	30	1600	93	850	103	38
8/17/2024	0.198180475	30	1600	94	860	102	38
8/18/2024	0.180032929	30	1600	91.5	770	102.5	40
8/19/2024	0.167242565	30	1600	90	780	103	40
8/20/2024	0.188816715	30	1600	90	800	102	41
8/21/2024	0.172300517	30	1600	87	790	103	36.5
8/22/2024	0.221134592	30	1600	90	820	102	41
8/24/2024	0.112818638	30	1600	89	780	102	37
8/26/2024	0.107057945	30	1600	90	900	105	33
8/27/2024	0.159365239	30	1600	93	920	103	34
8/28/2024	0.166588173	30	1600	90	960	105	35
8/29/2024	0.117350881	30	1600	91	910	105	33
8/30/2024	0.129360978	30	1600	91	870	106	31.5
8/31/2024	0.138308418	30	1600	94	900	105	35.5
9/1/2024	0.188553886	30	1600	90	950	106	37
9/2/2024	0.160689669	30	1600	98	960	105	37
9/3/2024	0.445029831	30	1600	92	1100	105	39.5
9/8/2024	0.141629565	30	1600	91	880	100	37
9/9/2024	0.130040336	30	1600	98	860	100	35
9/10/2024	0.136907762	30	1600	90	800	102	37
9/11/2024	0.121501333	30	1600	93	750	103	35
9/12/2024	0.145600602	30	1600	89	800	103	36
9/14/2024	0.155811941	30	1600	95	840	100	39
9/15/2024	0.152229278	30	1600	96	815	105	37
9/16/2024	0.127240143	30	1600	99	830	106	37
9/17/2024	0.120994097	30	1600	90	900	105.5	37
9/18/2024	0.11592592	30	1600	91	880	105	36
9/19/2024	0.260404258	30	1600	93	950	105	39



SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.36012
R Square	0.129686
Adjusted R Square	0.067521
Standard Error	0.084351
Observations	61

ANOVA

	df	SS	MS	F	ignificance F
Regression	4	0.059373	0.014843	2.086153	0.094759
Residual	56	0.398447	0.007115		
Total	60	0.45782			

	Coefficients	andard Errc	t Stat	P-value	Lower 95%	Upper 95%	ower 95.0%	Jpper 95.0%
Intercept	-1.229217	0.855424	-1.436968	0.156291	-2.942838	0.484403	-2.942838	0.484403
Head Pressure	0.001043	0.004176	0.249691	0.80374	-0.007322	0.009407	-0.007322	0.009407
Dozer Speed	0.000262	0.000157	1.67125	0.100252	-5.21E-05	0.000577	-5.21E-05	0.000577
Boiler Temmperature	0.006068	0.007217	0.840808	0.404031	-0.008389	0.020525	-0.008389	0.020525
Hanging Stands Spee	0.012341	0.004856	2.541594	0.01383	0.002614	0.022068	0.002614	0.022068

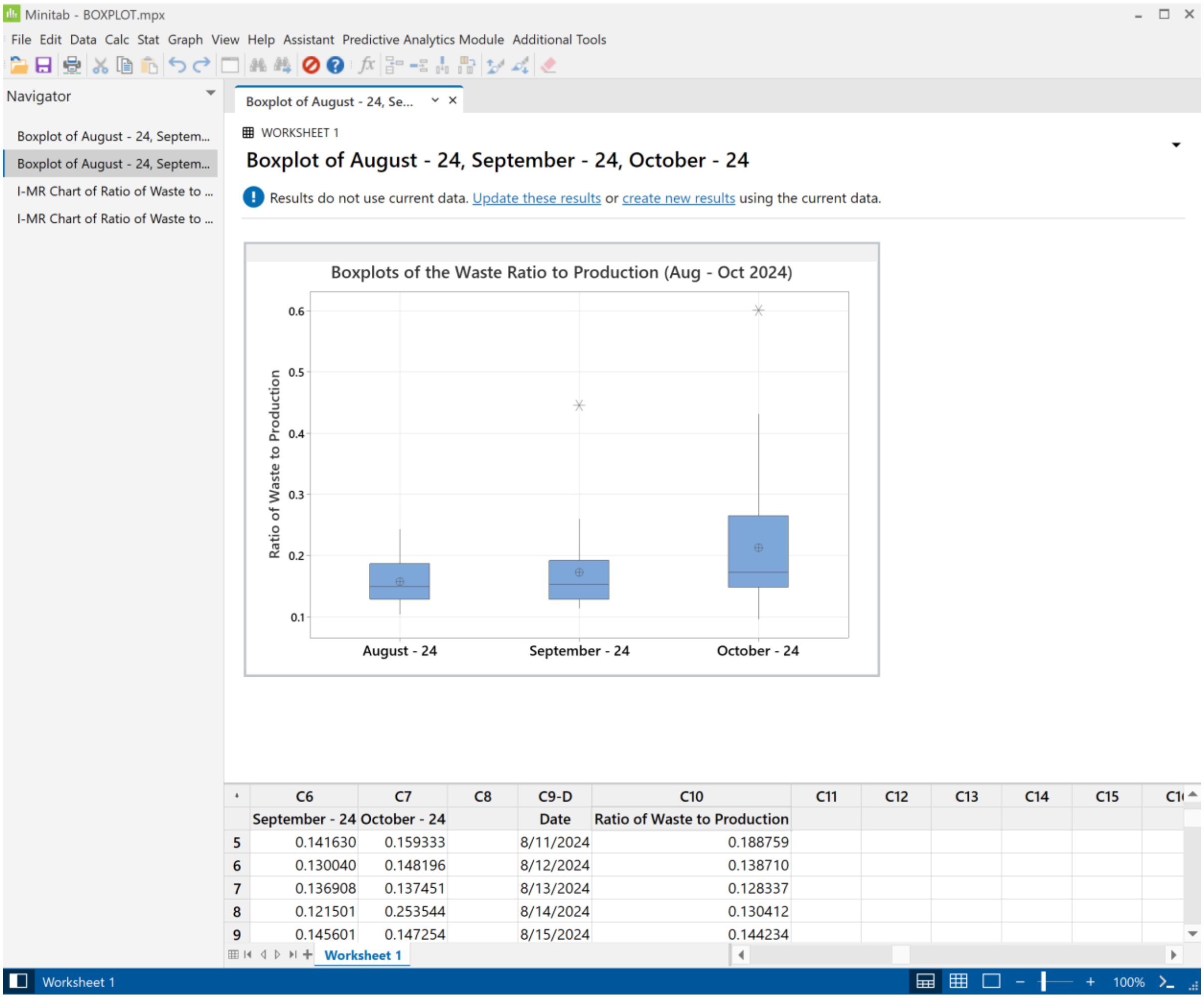
RESIDUAL OUTPUT

Observation	Vaste-Produ	Residuals	ıdard Residuals
1	0.25523	-0.034976	-0.429203
2	0.140437	-0.016703	-0.204969
3	0.168078	-0.032877	-0.403448
4	0.241549	0.001632	0.020027
5	0.187959	0.0008	0.009821
6	0.168247	-0.029537	-0.362461
7	0.173254	-0.044917	-0.551185

PROBABILITY OUTPUT

Percentile	-Production Ratio
0.819672	0.095434
2.459016	0.107058
4.098361	0.112819
5.737705	0.113492
7.377049	0.115926
9.016393	0.117351
10.65574	0.120994

Appendix B – Minitab Analysis (Control Charts, Boxplots, DoE etc.)



Appendix C – Power BI Analysis (Bubbles Plot)