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# Stochastic Modeling of Throughput-Quality Dynamics in Labor-Intensive Manufacturing: A Comparative Analysis of Operator Fatigue and Process Instability

**Md. Muqtadir Fuad, Abdullah Al Mazid, Md. Istiak Adnan and Khalid Ammar**
Department of Industrial and Production Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
2008079@ipe.buet.ac.bd, 2008080@ipe.buet.ac.bd, 2008114@ipe.buet.ac.bd, 2008089@ipe.buet.ac.bd

## Abstract

The inherent variability of manual assembly process possesses significant challenges to standardization and quality assurance within semi-automated food production sector. The study presents a quantitative and comparative analysis of stochastic nature of human fatigue that affect the productivity. By integrating high resolution time motion analysis along with statistical process control (SPC), this research has dived into two manual production line to quantify quality parameters, find relationship among product shape, operator performance behavior, efficiency and unit weight consistency. We employed regression analysis to estimate the relationship between time and worker fatigue in a controlled environment. Furthermore, process capability analysis reveals the relationship of human fatigue and process instability. Finally, using Monte Carlo algorithm, we have simulated the data to quantify the annual financial loss due to process instability.

## Keywords
Human Fatigue, Monte Carlo Simulation (MCS), Stochastic, Quality, SME

## 1. Introduction
In South Asian developing countries, small- and medium-sized (SME) food manufacturing industries are a key part of the regional economy. As food manufacturing industries are highly process-oriented, this sector depends on human labor (Rahman et al., 2024). The world economy is changing rapidly with the newly developed automated systems and shifting from Industry 4.0 towards Industry 5.0. However, due to high initial cost and uncertain ROI, these industries in these countries are very cautious about adopting fully automated systems (Muzondo & Jokonya, 2023). In addition, the characteristics of the market (ethnic niche, small batches) also make automation difficult.

Culinary preferences in this region are very sophisticated compared to the other parts of the world. Specifically, the export target market of these food products also depends on the ethnic identity. Consequently, the expatriate communities living abroad are mainly the consumers of these food items. Hence, instead of large-scale orders, companies are interested in taking small- or medium-sized orders to meet that particular customers' needs. This demand for customized, small-batch production increase product variability which limits the integration of automation in this sector.

Moreover, the food materials used in production are soft and variable in shape, size, and characteristics. These variabilities are difficult to handle for robotic arms. Flexible automation equipment is very expensive and complex in the context of the South Asian economy. Besides, the average wage of a worker is approximately BDT 230 per working day. In practice, informal and lower-skilled workers are paid even lower daily rates. This entire socio-economic scenario of this region has pushed the industries to become human labor dependent. This heavy reliance on human labor creates significant challenges, as the human body has a physical work constraint. Repetitive movement of muscles causes fatigue, muscle injury, or long-term physical strain. Because of these human-oriented physical constraints, the efficiency of production lines drops significantly.

The problem existing in that system is that in most industries the management does not consider human factors. As a result, many of the industries runs sub-optimally. Mostly, the management use an unrealistic 'deterministic' approach (Bendul & Knollman, 2016), which assumes that human labor will provide a steady and stable production rate over the entire timespan (Kanawaty, 1992). As a result, the production plans in these SME food industries are facing a prominent gap between their calculated capacity on paper and the actual capacity on the production floor.

The inherent incompatibility between deterministic production targets and the stochastic reality leads to an ineffective production planning as physically fatigued human operators cannot maintain a linear curve of production. This implies that there are two ways of failing in this case: ***Fatigue Drift***: The cycle time slows down as a result of physical exhaustion of operators; ***Process Instability***: Occasions when the operators become manic in trying to meet quotas and the productivity levels which fails to meet quality parameters. One of the quality parameters is the process capability ($C_{pk}$)**.** When a product that exceeds its minimum weight specification, the process becomes incapable. This variation process capability ($C_{pk}$) that results in financial losses due to raw material 'giveaway' (when it exceeds the upper specification).

Several studies focused on human fatigue modeling and quality control in food processing separately. However, a few numbers of researches address the association (or Speed-Accuracy Trade-off) between the two is quantified in the manual SMEs. The research is also yet to determine extant studies utilizing the stochastic model to measure direct correlations between PMV and material loss in labor-intensive settings. This research closes this gap with the help of parametric Monte Carlo simulation where we have modeled the operational effects of fatigue and natural variability of the operator in economic terms.

The research tries to find out answers to the following questions:

1. How does human fatigue change over time in a controlled environment? And if it does, what is the rate of change?
2. Is there any relation between human fatigue and process variability? Does human fatigue have any impact on product quality and losses? Does process stability depend upon human fatigue?
3. How much does it impact an industry financially? Can we approximate the loss due to these stochastic human factors?

## 2. Literature Review

Human fatigue is a complex physical and psychological phenomenon that many scientists have tried to explain and determine, especially in regard to physical work activities. And it is said to be a subjective feeling of discomfort that is generated by a variety of reasons, including inadequate sleep, long working hours or excessive overtime, high cognitive and physical workloads, monotonous or complex task demands, etc. (Guo et al., 2021). Vernon (2022) explains that operator fatigue influences efficiency and also impacts the overall industrial profitability. Yung et al. (2019) concluded that fatigue accounts for up to 42% of quality deficits variance. So, it becomes important to determine the operator's fatigue in the correct way. Over a long period of time, researchers had used fatigue allowances to measure the operator fatigue, where fatigue allowance indicates a function of operator work efficiency. Previously it was used as a percentage of the normal time for only the effort or manual work time (Das, 1990b).

In many production processes workers do not work continuously; they may stop their tasks due to various factors. For these kinds of production processes, fatigue allowance is very difficult to obtain accurately. So, numerous research studies proposed using stochastic processes as well as Monte Carlo simulations to model and analyze human fatigue (Lucchese et al., 2023, Jamshidi, 2019, Al-Araidah et al., 2020). For example, Mendes et al. (2016) applied Monte Carlo simulation to production lines with stations experiencing variability in processing time due to the human factor. By integrating Monte Carlo uncertainty with multi-component fatigue modeling, Ding and Cui (2025) developed a stochastic framework to capture the inherent variability in human biomechanical performance, which deterministic models fail to address.

While stochastic models capture the randomness of fatigue, the rate of fatigue is also dependent on the complexity of the product. Meštrović et al. (2025) argue that perceived operator workload is a crucial, non-linear accelerator of human fatigue and that product complexity goes beyond structural design. This accelerated fatigue becomes critical when operators in the production process rush to meet throughput targets, as the combination of high complexity and speed significantly increases error rates, thereby hampering the quality of the product. Prior research shows that higher operating speeds do not necessarily improve throughput because they often increase rework and, as a result, decrease the product quality (Owen & Blumenfeld, 2008).

Production cost and profit is closely related to these operational dynamics. While increasing line speed (throughput) initially boosts revenue, research on the "Cost of Quality" shows that the costs of scrap, rework, and waste disposal frequently result in a diminishing return. So, this study considers stochastic analysis as well as Monte Carlo simulation to better understand and model the throughput-quality dynamics in a manual food assembly line where operator fatigue, production speed, quality, and revenue are of great concern.

## 3. Methodology

### 3.1 Experimental Setup and Data Collection

The data were collected from a controlled environment of Bangladeshi frozen food manufacturer. The temperature, humidity and lighting of the factory were controlled by central air-cooling system and humidity controller. Hence, the effect of temperature to the workers fatigue can be assumed negligible as the temperature and humidity both are maintained strictly to 18 $^0$C and 50-55%. For this study we choose two products (Figure 1):

i. **Product A**: Complex shape and high value
ii. **Product B**: Simple shape and mass production

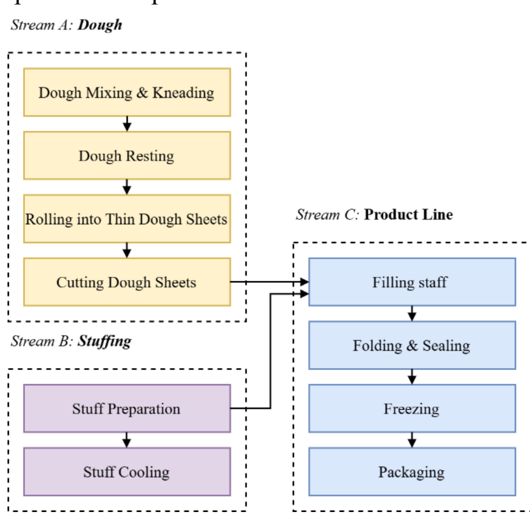



Figure 1. Process flow diagram of the entire process showing all the stream from the beginning to the packaging stage of the final product.

Both of these products are manufactured in multiple lines. However, we took two lines for our study purpose. Most of the processes of the facilities to manufacture those products are highly manual as well as process intensive. It can be characterized by high-frequency, repetitive manual assembly. The process includes three major parts: cooking of stuffs, filling and sealing the stuffs, freezing for both of the products.

As the entire process is totally manual, from cooking of stuffs to freezing, that's why the human involvement in the process make the processes more complex and volatile including value added and non-value-added activity. The nature of the process has made it inherently stochastic, along with the cycle time and accuracy influenced by the fatigue of workers and their per minute value. Operators perform volumetric dosing using hand followed by a complex manual folding sequence to seal the semi-solid filling within the dough sheet.

Data collection was stratified into two product groups. For the product of group A, data was collected from the mid-morning shift, where cycle time (per batch/tray, where 55 products were manufactured per cycle) was recorded along with a stopwatch and digital weighing scale ($\pm$ 0.1 $g$) to assess fatigue drift, and a total of 99 samples were collected randomly from both lines (Table 1) to evaluate and compare line capability. For group B, which is basically simple in structure, per minute value was recorded to analyze production stability along with 63 samples collected to measure line capability like the previous process and additional 45 samples for post-freezing to quantify moisture dynamics.

The data was recorded from two lines of both products. The description of collected data is presented as belowin Table 1:

Table 1. Summary and description of collected data from production line

| Product (Target) | Geometric Complexity | Variables Observed | Sample Size (N) |
|---|---|---|---|
| Product A (75 g) | Complex | Cycle Time (Drift) | 10 Batches |
| | | Product Weight | 99 Units |
| Product B (10 g) | Simple | Throughput (PMV) | Continuous Log |
| | | Product Weight | 63 Units |
| | | Frozen Weight | 45 Units |

### 3.2 Statistical Characterization

Shapiro-Wilk is a statistical testing method to validate whether the sample weights follow a proper normal distribution (Shapiro & Wilk, 1965). Shapiro-Wilk test was applied ($\alpha = 0.05$) to determine if weight distributions followed a Gaussian profile:

$$W = \frac{\left(\sum a_i x_{(i)}\right)^2}{\sum (x_i - \bar{x})^2} \dots\dots\dots\dots\dots\dots (1)$$

For sample sizes $N > 50$, the coefficients $a_i$ were approximated using the expected values of standard normal order statistics ($m_i$), derived via Blom's plotting position formula (Downton, 1961):

$$a_i = \frac{m_i}{\sqrt{\sum m_j^2}}, \quad \text{where } m_i = \Phi^{-1}\left(\frac{i - 0.375}{n + 0.25}\right) \dots\dots\dots\dots\dots\dots (2)$$

The assumption of equal variances was between two production lines was tested using Levene's test for homogeneity of variance where the alternative hypothesis confirms the difference of at least one variance. Unlike Bartlett's test, Levene's test is robust to deviations from normality, making it suitable for the small-sample, discrete weight data observed in this study (Bartlett, 1937, David et al., 1961) to check the speed-accuracy trade off.

To understand the true nature of the linear fatigue model, we adopted Durbin-Watson (DW) statistic to validate the workers' fatigue. DW test checks the autocorrelation among the residuals whether the observed efficiency decay follows a systematic linear trend or is driven by complex, autoregressive patterns that a simple linear model cannot capture (Durbin & Watson, 1971). Human fatigue is often complex and stochastic in nature where it is assumed that it increases over time, but the true unpredictable nature can be determined by analyzing the residuals. DW value in the range of 1.5 to 2.5 is accepted to be the rule of thumb to indicate in independence of the residuals (Draper & Smith, 1998).

## 3.3 Stochastic Modeling Framework

Two distinct mathematical frameworks were established to characterize the probabilistic behavior of operator performance and the resulting material loss:

**Operator Fatigue Dynamics**

Operator efficiency decays overtime. We have characterized this efficiency loss by a non-stationary linear trend model. This model separates the deterministic fatigue component from random process noise:

$$y_t = \beta_0 + \beta_1 t + \epsilon, \quad \epsilon \sim N(0, \sigma^2) \text{ ……………… (3)}$$

$y_t$ denotes the cycle time for the $t$-th production batch (tray). $\beta_0$ is the intercept referring to the operator's initial speed; $\beta_1$ is the slope, represents the 'fatigue rate' or efficiency loss per tray. $\epsilon_t$ denotes stochastic variability, assumed to follow a Gaussian distribution $\epsilon \sim N(0, \sigma^2)$.

**Process Capability and Material Giveaway**

The process incapability has a negative impact over business. The financial loss and impact over business by caused by material overfilling are characterized and quantified by the process capability index, $C_{pk}$.

$$C_{pk} = \min\left(\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right) \text{ ……………… (4)}$$

A negative $C_{pk}$ value indicates that the process mean($\mu$) has shifted beyond the specification limits. It confirms the material overfilling than random error.

## 3.4 Parametric Monte Carlo Simulation

Monte Carlo algorithm has been used to simulate data points to extrapolate the short-term findings into a long-term operational risk assessment (Metropolis et al., 1953). This computational method generates synthetic data points to predict the aggregate financial impact of process instability and overfilling. Parametric Monte Carlo simulation was performed using python which utilizes the NumPy (Mersenne Twister algorithm) to create stochastic variables based on the probability density functions (PDFs) recognized in the empirical analysis (Matsumoto & Nishimura, 1998). This method has probabilistic extreme outliers, unlike simple extrapolation, that might impact quality costs.

**Simulation Parameters**

The simulation was performed for 10,000 iterations per product line to convergence and minimize standard error in the output estimation. Cycle time and product weights are considered as input variables. These variables were generated using the specific mean ($\mu$) and standard deviation ($\sigma$) derived from the pilot study data. The observed variance characteristics have been kept intact in this simulation model.

**Financial Loss Model**

We employed a custom loss function to quantify the financial loss due to the 'material giveaway'. This model is constructed based on non-symmetrical financial penalty; where underweight isn't incurring loss whereas overweight results in financial loss. The Annualized Financial Loss (AFL) is calculated as follows:

$$L_{financial} = P_{annual} \times \frac{1}{N}\sum_{i=1}^{N}[\max(w_i - T, 0) \times C_{mat}] \text{ ……………… (5)}$$

The equation represents financial loss incurred from process instability where $P_{annual}$ is the projected annual production volume; $w_i$ is the simulated weight of the $i$-th unit; $T$ is the Target Weight (10g or 75g); $C_{mat}$ is the unit cost of the raw material filling (Currency/gram). The function $\max(w_i - T, 0)$ ensures that only positive deviations (overfill) contribute to the cost accumulator. Sensitivity analysis varied $\mu$ and $\sigma$ by ±10-20% to assess robustness.

# 4. Results

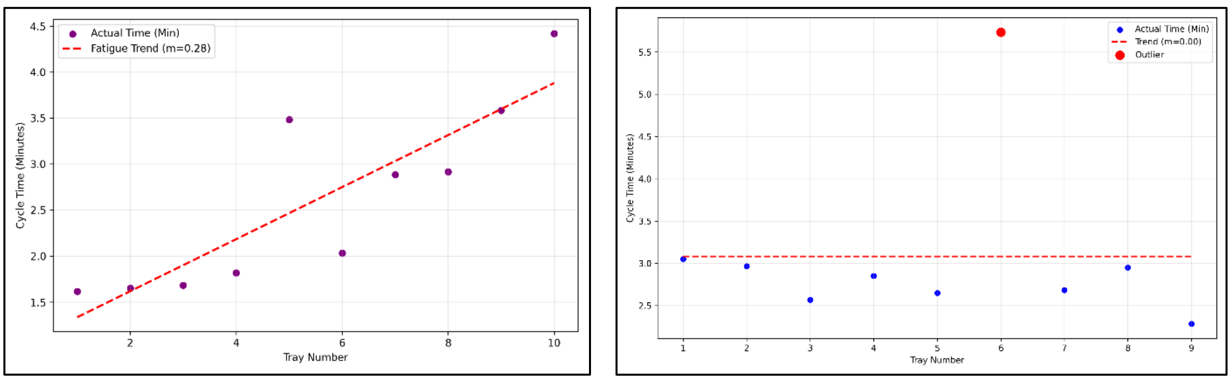
## 4.1 Product A: Physiological Fatigue vs. Process Instability

A comparative evaluation between Line 1 and Line 2 was performed to identify differences in performance stability, fatigue progression and quality consistency during the production of product A which have been summarized in Table 2.

Table 2. Comparative statistical analysis of temporal and quality dynamics (Product A)

| Statistical Metric | Line 1 | Line 2 |
|---|---|---|
| **Fatigue Rate (β)** | $+0.2827\ min/tray$ | $+0.0000\ min/tray$ |
| **Model Fit ($R^2$)** | 0.7433 | 0.0000 |
| **Autocorrelation (DW)** | 2.5904 | 2.3448 |
| **Weight Normality ($p$)** | 0.3003 (Normal) | 0.0200 (Not Normal) |
| **Primary Failure Mode** | Physiological Fatigue | Process Instability |

Line 1 demonstrated a clear fatigue-induced escalation in cycle time, reflected by a positive fatigue gradient β = +0.2827 min/tray, with a substantial model fit of $R^2 = 0.7433$, confirming that nearly 74% of cycle-time variation can be attributed to the tray count. This establishes the presence of a time-linked degradation in operator performance.

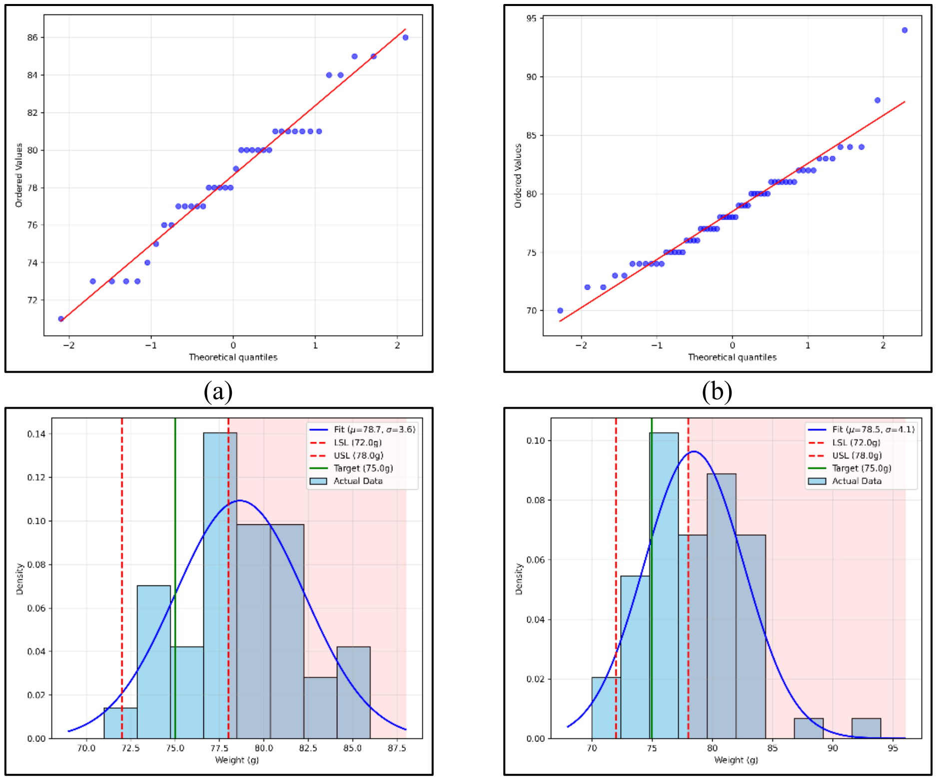



(a) Line 1 (b) Line 2

Figure 2. Fatigue analysis of (a) line 1and (b) line 2 for 'Product A', where line shows fatigue trend of +0.2827 min/tray and line 2 shows a horizontal line

The DW statistics value is 2.5904 which is greater than 1.5 (Figure 2), indicate that there is no autocorrelation among the residuals of the trend line. It also confirms that fatigue progresses stochastically rather than linearly, the operator slows down overall, but with fluctuations in between cycles. We found that the Shapiro-Wilk p-value of weight measurements for line 1 is 0.3003, confirming that weight is normally distributed and it also validate the use of parametric capability indices. Overall, physiological fatigue is the main dominant cause of line 1's failure.

In contrast, Line 2 showed no measurable fatigue progression (β ≈ 0.0000) and effectively no regression model strength ($R^2 = 0.0000$). this indicates that cycle durations did not deteriorate with tray count. Instead of a linear fatigue trend, the Durbin-Watson value of 2.3448 confirms residual independence, meaning performance fluctuations were random rather than cumulative. This behavior can be explained by how the shift was worked. The worker on Line 2 took small micro-breaks during the shift, which helped the worker to reduce fatigue instead of letting it build up over time. Because of these short breaks, the cycle time does not show the usual steady increase that happens when someone gets tired. Also, the small amount of data makes it harder to clearly see any small trends that might be hidden by noise.




(a) (b)

(c) (d)

Figure 3. Process capability $\left(C_{pk}\right)$ analysis of product A. **(a)** Q-Q plots for normality check for line 1 **(b)** Q-Q plots for normality check for line 2 **(c)** Line 1 capability; indicating overfilling**.** The process mean($\mu = 78.7$g) has shifted beyond the Upper Specification Limit (78.0g), resulting in a high volume of non-conforming units (red zone) despite a target weight of 75.0g. **(d)** Line 2 capability; indicating overfilling**.** The process mean($\mu = 78.5$g) has shifted also.

Line 2 has constant temporal behavior. But the weight distribution of the products from this line didn't show normal weight distribution (p = 0.02), indicating a skewed and uneven fill mass. This shows that physical tiredness is not the main cause of variation. Instead, the variation comes from process level instability such as uneven dough filling, changes in how the stuffing is held, non-standard movements, or weight differences between batches (Figure 3).

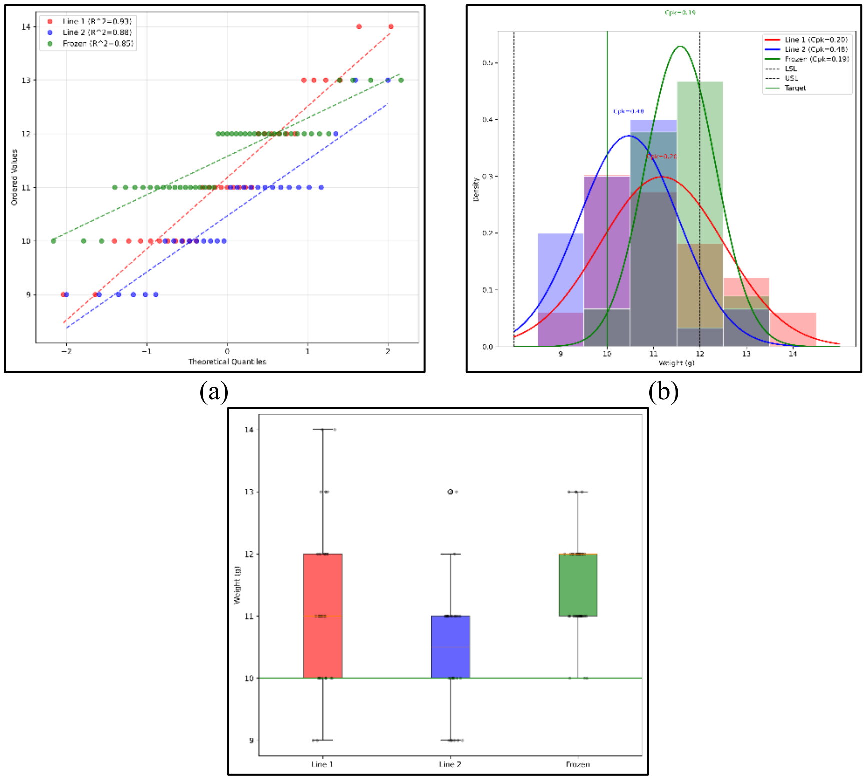
In this situation, the worker's short breaks stop fatigue from building up, but differences in handling or material flow still cause the product weight to change unpredictably. Thus, in Product A processing, constraint in line 1 is fatigue, whereas Line 2 is precision-constrained, driven by intermittent rest intervals, lower sample density, and higher inconsistency in material deposition rather than endurance decline.

## 4.2 Product B: Process Capability and Weight Precision Deviations

In this study, we've observed the production of product B from both 'Line 1' and '2,' as well as the frozen batch. In all these three cases the weight distribution found is not normal Gaussian.

This non-normal distribution indicates that the process for this product is highly sensitive to the operator's technique, how tightly the material is packed, the dough's elasticity, and how the stuffing flows. Because of these factors, the amount filled becomes inconsistent instead of forming a smooth and stable pattern. The average weight found after analyzing from line 1 is 11.18 with a variation of 1.33.

It exceeds the target mean by 11.85% and the variability is large. This high speed, along with a low p value (0.0178), identifies the process ass unstable and dependent on the operator. The capability index $C_{pk} = 0.205$ confirms that many samples cross the specification limits, showing that the filling process lacks proper flow control and consistency (Figure 4).




(a) (b)

(c)

Figure 4. Process capability analysis for product B showing **(a)** Q-Q plot comparing model fit ($R^2$) for Line 1 (Red), Line 2 (Blue), and Frozen (Green). **(b)** Histogram showing process centering and capability indices ($C_{pk}$). **(c)** Boxplots illustrating weight distribution, medians, and outliers across the three production stages.

Line 2 showed slightly better control, with a mean of $\mu = 10.47\ g$, which is 4.7% above the target, and lower variation ($\sigma = 1.07\ g$) compared to Line 1 (Figure 5).

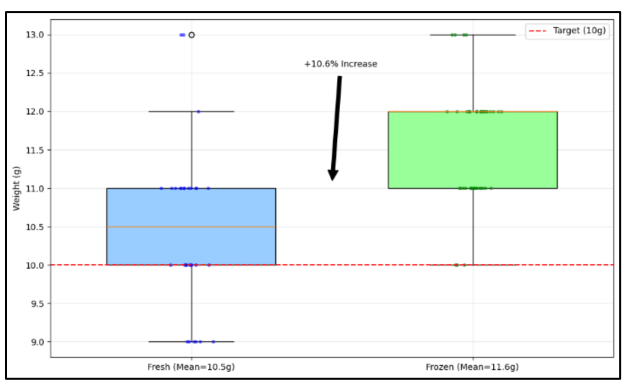



Figure 5. The boxplot compares Fresh ($\mu = 10.5$g) and Frozen ($\mu = 11.6$g) samples, revealing a 10.6% increase in mean weight due to ice accretion. Note that the entire interquartile range of the frozen batch (green) has shifted above the 10.0g target line (red dashed), indicating overfilling.

Line 2 performed better but the weight distribution was not normal ($p = 0.0021$) and the capability was low ($C_{pk} = 0.476$). this indicates that line 2 reduced some extra filling but still could not center the process or make the weights balanced. The operator corrected some issues, but not enough to make the process stable or prevent the weight from being skewed.

Data pattern of the frozen batch was different. Average weight was 11.58g with variation 0.75 g. but the worst thing is that it was overfilling at 15.8% above the target. It was noticed that the freezing process makes the product heavier than the before freezing product. It is because of the creating ice layer. This lowers the variation, but it forces to push the average weight beyond the acceptable limit. Its capability index is the lowest of all stages which means that freezing makes the errors worse even if the variation looks controlled. Overall, Product B is not hampered by worker fatigue the way Product A is. Instead, it has accuracy and precision problems at every stage of production. Whether the product is fresh or frozen, maintaining the correct weight is the biggest issue. The weight the product B inconsistency happened because the product is very sensitive to the amount of stuffing and how much water it absorbs. To fix this, the process needs controlled filling equipment, better moisture management, and stricter process standards to meet quality requirements.

## 4.3 Economic Loss and Sensitivity Analysis

Based on the parametric monte carlo simulation this study quantifies the financial indication losses of the product lines. The financial impacts are assessed using a non-symmetrical loss function that penalizes material "giveaway" (positive deviations from the target weight).

### 4.3.1 Monte Carlo Simulation Results

Monte Carlo simulation has been quantified the annual economic implications of overfill or material loss due to quality failure. Product A contributes an estimated 1,329,302 BDT, while Product B accounts for 366,971 BDT due to 6,647 kg of product A and 1,835 kg production loss respectively. The industry combinedly loses nearly 1.7 million BDT annually, not from direct rejects but rather from continuous material giveaways. This highlights that weight variability is a quality risk, and it also erodes profit (Figure 6).

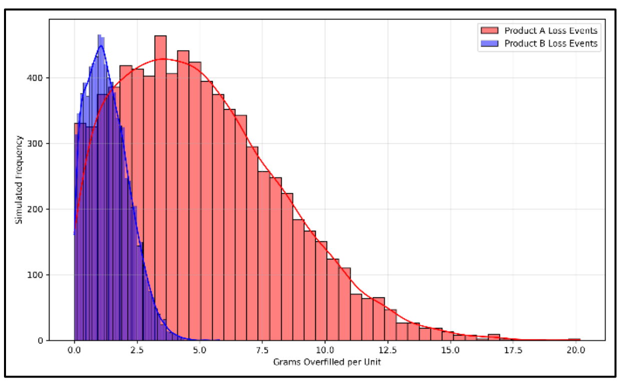
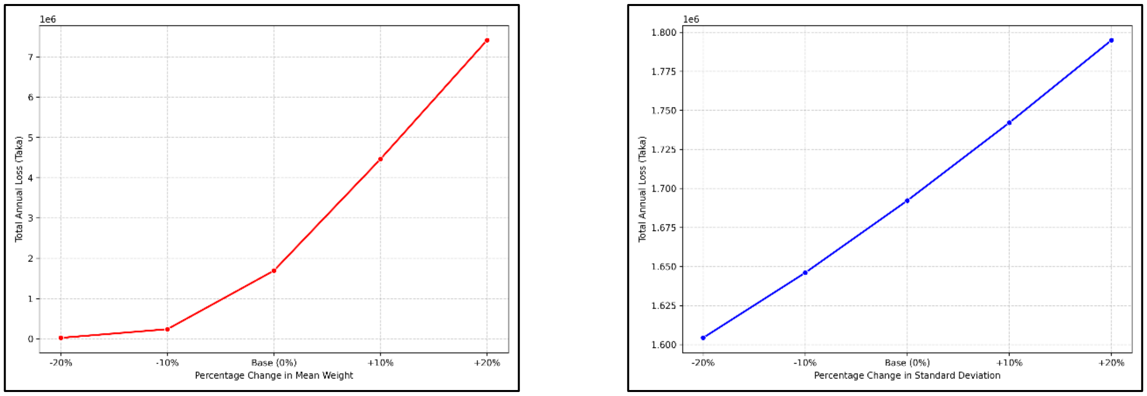



Figure 6. Simulated distribution of overfill magnitude for Product A (Red) and Product B (Blue). The x-axis represents the excess grams per unit given away

### 4.3.2 Sensitivity Analysis

We have conducted a sensitivity analysis by varying the mean (μ) and standard deviation (σ) by $\pm 10\%$ and $\pm 20\%$ to assess the robustness of the financial projections according to the estimation. This analysis points out the key factor that drastically impacts the factory's bottom line.

The total loss is very sensitive to shifts in the process mean than the standard deviation. A 20% increase in mean weight causes the annual loss to surge from BDT 1.69 million to BDT 7.41 million. Changes in Standard Deviation (process spread) have a significant but comparatively linear impact on total loss. This analysis directly addresses the root cause of the problem (Figure 7, Table 3).




**(a)** **(b)**

Figure 7. Sensitivity Analysis of Total Annual Financial Loss relative to (a) Percentage Change in Mean Weight with a fixed standard deviation and (b) Percentage Change in Standard Deviation with a fixed process mean.

Table 3. Sensitivity Matrix of Total Annual Financial Loss relative to Deviations in Mean Weight and Standard Deviation

| Change (%) | Total Annual Loss (Varying Mean, in BDT) | Total Annual Loss (Varying Std Dev, in BDT) |
|---|---|---|
| -20% | 24,406 | 1,604,324 |
| -10% | 239,006 | 1,646,004 |
| Base (0%) | 1,692,209 | 1,692,209 |
| +10% | 4,461,647 | 1,742,113 |
| +20% | 7,412,181 | 1,794,923 |

## 5. Discussion

The comparative analysis of two distinct type of frozen food products in two different manual processing lines is presented in this section. The behavioral mechanics of workers have been assessed from different angle in this comparative study. The findings demonstrate that productivity output is not only function of production speed, rather a mixed and complex interaction of shape and size of product, workers fatigue, stability, environment and distribution symmetry what challenges the assumption of higher throughput with better efficiency.

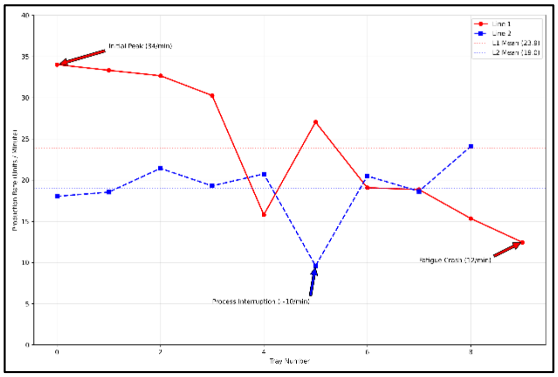
### 5.1 Fatigue, Instability and Precision Failure

In line 1, we can see a gradual trend in cycle time. This increment in cycle time indicates physiological fatigue accumulation over production duration as well as repetitive workload. Though the performance of workers slowed down but the system remained normally distributed in weight. It denotes that the workers in that time and line maintained consistent technique even under increasing exertion. Intermittent micro-resting patterns (including non-value-added time) and a smaller data window for the second line might prevented workers' fatigue from compounding. Though having better steadiness over time, Line 2 exhibited unstable weight behavior, leading to quality control failure. This observation in both lines confirms the inconsistency due to speed without stability whereas more controlled performance in another line.

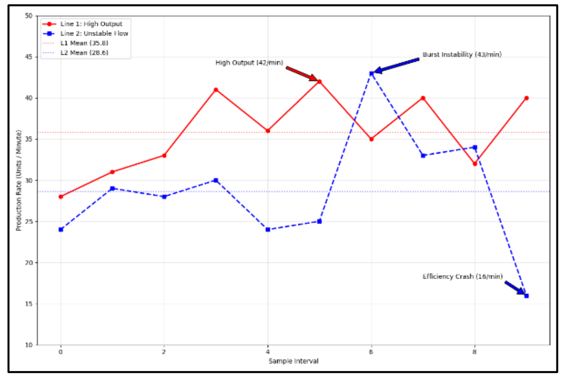
Both Product A and Product B displayed non-normality regardless of processing state, Line 1, Line 2, or frozen storage. Hand-filling error is more sensitive for smaller SKUs, resulting in offsets of +11.8%, +4.7%, and +15.8% above target. The frozen batch exhibited the lowest variation yet the highest mean deviation, confirming that moisture retention artificially inflates mass and compresses spread. This suggests that for smaller SKUs, precision of deposition is more critical than temporal behavior. The failure mechanism is volumetric and moisture-driven, not time-driven.

### 5.2 The Economic Cost of Overfill and Process Capability Breakdown

The parametric Monte Carlo Simulation in subsection 4.3.1 and sensitivity analysis part 4.3.2 reveals how process variability can attribute to the economic loss. Specially, the sensitivity analysis part reflects that economic loss is highly responsive to mean shift in such manual labor-intensive industry with a 20% increase escalating annual costs from BDT 1.69 million to BDT 7.41 million. Across both products and all conditions in this study, quality parameter(weight) remained well below acceptable thresholds. It both violates process quality for not meeting specification parameters and incurs financial losses (Figure 8).




(a)




(b)

Figure 8. Throughput dynamics for **(a)** Product A and **(b)** Product B. The plots compare the operational behaviors of Line 1 (Red, exhibiting fatigue trends) versus Line 2 (Blue, exhibiting stochastic instability) across production intervals.

Crucially, this analysis clarifies the relationship between worker fatigue and process capability. For Product A, Line 1 and Line 2 were guided by opposing failure modes, fatigue vs. instability, and ultimately resulted in process capability deficiency. Product B also supports this observation for product A. Apart from it, it shows that process centering and distribution symmetry are not under statistical control. The fact that the non-fatigued line (Line 2) also failed to meet specifications demonstrates that physiological fatigue is an exacerbating factor, not the root cause. Fatigue increases the spread of the variance (higher standard deviation), but the fundamental inability to meet the $\pm 2g$ tolerance is inherent to the manual volumetric filling method itself. So, the root cause of non-conformance lies in the deviation of material filling that is attributed to manual processing and the lack of a skilled workforce in every line. Designing a tool or semi-automated process might improve the accuracy instead of using hands to do the filling process.

### 5.3 Moisture & Thermal Artifact: Freeze-Induced Gain

Frozen batches of Product B gained approx. +15.8% mass due to moisture uptake/ice glazing. Though it reduces deviation, it worsens target overshoot. While this increases nominal yield, it degrades frying texture and shelf performance. For maintaining both weight compliance and sensory crispness, controlling humidity and boundary-layer freezing will be critical process control parameters. This study exemplifies that *quality retention per unit of labor* should be the factory efficiency rather than unit per hour.

## 6. Conclusion

This study provided a quantitative evaluation of the manual manufacturing dynamics within the ethnic frozen food sector. The results exhibits that the manual production environment is characterized by two distinct failure modes: deterministic physiological fatigue (Line 1) and stochastic instability (Line 2).

Although we have demonstrated that two of the lines are incapable of maintaining the quality parameter within the process, we can't conclude that worker fatigue entirely contributes to process incapability. The continuous failure of the non-fatigued line demonstrates that the manual filling method is the dominant constraint here. Besides, there is also a limitation of study time. Observing a longer period or a large number of days might result in a more accurate result and fewer discrepancies. One of the crucial limitations of our study is the time study of dissimilar products in two different shifts (i.e., product A in the morning or at the beginning of the shift and product B at the end of the shift or in the afternoon), which led to inconsistency while comparing the performance of the two processes (though they are quite similar). For instance, product A may produce a different result in the later shift. In this case, the estimation of financial loss might deviate significantly.

However, these are all options for future researchers in this field. The limitation of time, budget, and process study limits the scope of applying the application of this study to a broader scope; however, it initiates the path away from 'kaizen' in manual handling.

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## Biographies

**Md. Muqtadir Fuad** is a bachelor student in the Department of Industrial and Production Engineering of Bangladesh University of Engineering and Technology (BUET**)**. He has a strong interest on research in the field of ML/DL (NLP, LLM, ASR), Optimization, SQC and Computational Fluid Dynamics (CFD).

**Abdullah Al Mazid** is a B.Sc. student in the Department of Industrial and Production Engineering (IPE) at Bangladesh University of Engineering and Technology (BUET). His interests span a wide range of technology-driven and analytical fields, including programming, machine learning, system design, and practical problem-solving.

**Md. Istiak Adnan** is a B.Sc. student in the Department of Industrial and Production Engineering (IPE) at Bangladesh University of Engineering and Technology (BUET). His research interests are broad and deep, covering areas such as artificial intelligence, machine learning, manufacturing engineering, operations management, quality control and supply chain management.

**Khalid Ammar** is a final-year undergraduate student in the Department of Industrial and Production Engineering (IPE) at the Bangladesh University of Engineering and Technology (BUET). His research interests primarily focus on Supply Chain Management, Statistical Quality Control, and Computational Fluid Dynamics (CFD).