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Downtime Analysis of a Mayo Bottling Line During the Ramp-Up Period: A Case Study

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Abstract

Manufacturing companies face many challenges when trying to meet the market and their clients' demands. Building and operating highly automated lines is not a straightforward task, especially when the bottle format is unique, and the line is being built from the ground up to accommodate the new format. In this study, downtime data and Overall Equipment Efficiency (OEE) analysis was used to determine the effectiveness of a newly built mayonnaise bottling line during the ramp-up period and the main reasons behind low OEE, a lengthy ramp-up period, and high downtime. Two pieces of machinery were the most significant contributors to downtime, a newly bought labeler, whose factory acceptance test (FAT) was never performed, and an old, repurposed drop packer, that was previously being used for a much larger packaging format. It was found that the two machines had the same MTTF (mean time to failure) value. A model was built to predict the likelihood of attainment loss using a Monte Carlo simulation after performing a goodness of fit analysis on the time-to-failure (TTF) and time-to-repair (TTR) data available. From this model, the availability of the line was determined, and the effect of the two equipment was shown to be strong on the overall performance of the line.

Keywords
OEE, Automation, Risk Analysis, Bottling, Manufacturing.

1. Introduction

The food and beverage industry is the second largest industry in all of Canada accounting for 17% of total sales in manufacturing (Government of Canada 2023). This sector has been growing consistently over the years and contributes significantly to the country's GDP (Wunsch 2021). This growth, combined with the increasing complexity and customization of customer demand, is adding pressure on designing and efficiently operating highly automated production lines. Automation reduces the number of operators needed on the line, and is mostly applied for monotonous, repetitive, and complex tasks (Zennaro et al. 2018). In addition to these challenges, food manufacturing companies in Canada must meet SQF requirements, which is the Food Safety Code of Manufacturing, and are assigned a rating based on compliance and a yearly Audit Score (The SQF Institute 2017). This will virtually determine the market share of a manufacturing company by strengthening (or weakening) its competitiveness and reputation.

The gold standard in today's industry for measuring manufacturing productivity is OEE (Overall Equipment Efficiency). OEE takes into consideration three factors: Availability, Performance, and Quality. A 100% OEE means there is no downtime, no waste, and the process is running as fast as possible. Seiichi Nakajima, the Japanese pioneer who defined OEE, asserted that OEE above 85% is ideal and is considered world-class (Nakajima 1988). Although this can be achieved, it is highly difficult and challenging, and only about 5% of manufacturing organizations have reached this level. This number is based on data from more than 50 countries (Devonshire 2022).

The subject of this paper is to analyze a Mayo bottling line at a food manufacturing company operating in Ontario during the ramp-up period, detect the main causes behind a low OEE, and propose solutions to eliminate waste and increase effectiveness. In this case, the mayonnaise bottling line, which will be referred to in this study as Mayo Line, is a completely new line being commissioned by the engineering department and handed over to the operations department. This study will highlight the major causes of downtime on the line, as well as evaluate the selection of the machines in terms of sophistication, newness, and compatibility with the other equipment on the line and with the product itself. A statistical analysis will also be performed to determine the failure modes of the most critical machines, and a model will be created to quantify the risk of affecting the line performance when using these machines.

After determining the major causes of a low OEE using a Pareto diagram, these causes will be analyzed using root cause methods. Then, solutions to resolve these issues will be presented. Section 1 of this paper will be dedicated to a literature review of OEE and general causes of inefficiency on a production line in normal production. Section 2 will detail the methods used for data collection and analysis. Section 3 will be around the case study itself. The entire process will be laid out workstation by workstation. In this particular case, the line being studied is still in a transition phase where two new machines have not been installed yet, and one hasn't been commissioned. These processes were replaced by other machines or methods in the interim. This study focus on the current, temporary phase of the project.

1.1 Objectives

In this research paper, the main goal is to analyze the performance of a mayonnaise bottling line in a manufacturing company in Toronto, and determine the main causes of downtime and low performance during the ramp-up period. These finding will then be used to determine whether the performance of the least efficient equipment can be predicted and avoided in future line designs and planning. Based on these findings, recommendations will be made as to what could be improved in terms of management and design decision when conceptualizing, building, and commissioning a new production line.

Different methods will be used to reach each objective, and these will be explained in the following Methodology section. A flow chart is used to illustrate all the detailed objectives of this papers, as well as the structure of the study. Each goal will be reached by using certain tools and methods, whose results will lead to the attainment of the next goal. Figure 1 below represents the mentioned flow chart.

The tools and methods will be explained in detail in the following section.

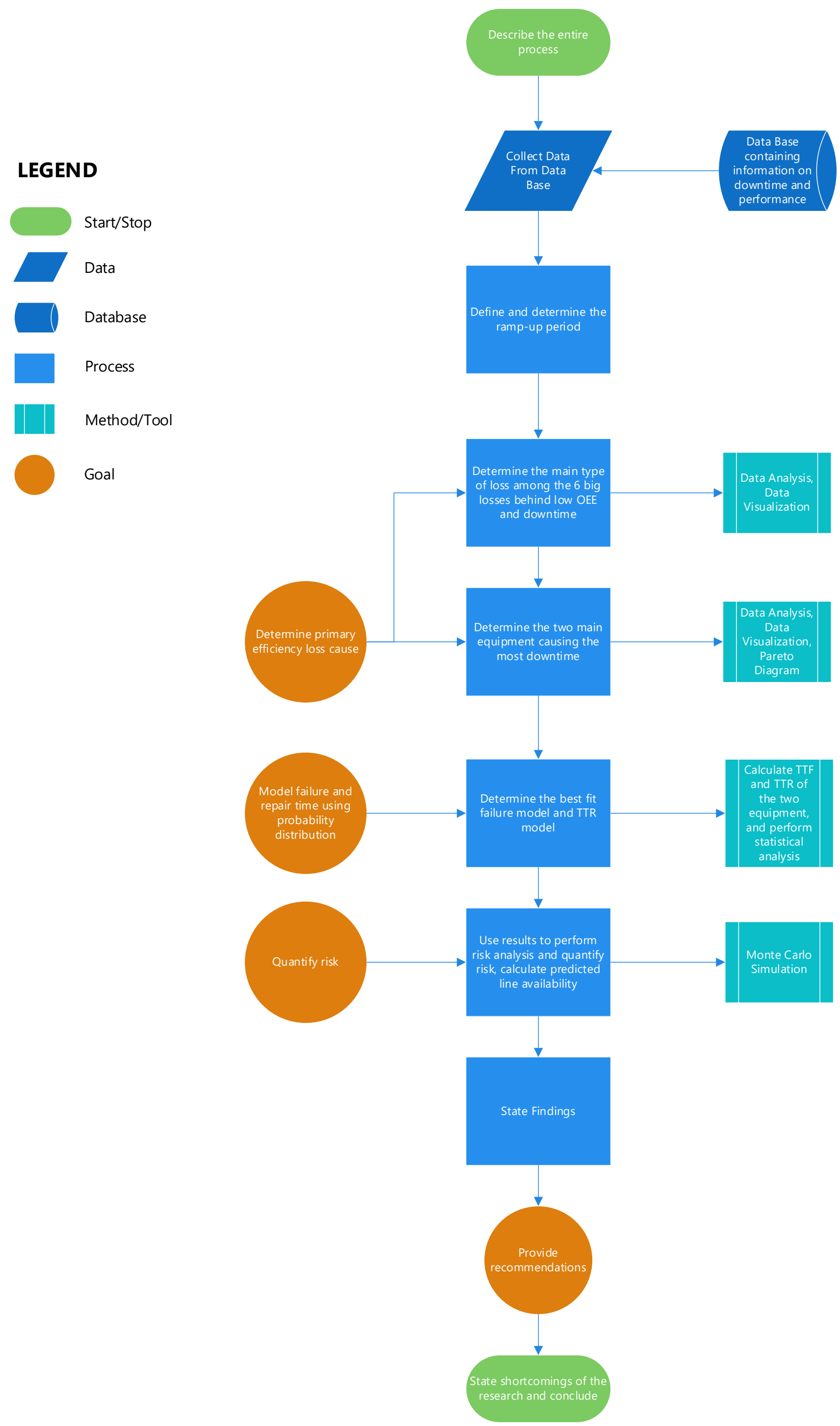

Figure 1. Objectives and Research Process Flow

2. Literature Review

The goal of the TPM concept is to eliminate breakdowns and defects originating from equipment. This will result in a significant increase in productivity and quality, eliminate waste, and reduce production costs (Muchiri and Pintelon 2008). A tool to measure this metric is OEE, which combines three factors: quality, availability, and performance. Using this tool helps identify the major areas of improvement and where capital and effort should be expended to improve productivity. A root cause analysis is essential when it comes to improving OEE, combined with a benefit-to-cost analysis to put a dollar value on the impact of investments.

In addition, classical OEE measurements, despite being the main tool to assess a production line or a piece of equipment, has its limitations. Flaws and limitations in the measurement instruments, the uncertainty and complexity of a production line, the failure to capture all the stops on the line and their durations, are some factors that cause fluctuations in OEE values and even inaccurate values. These factors might mislead managers into taking action based on wrong data as mentioned in a paper on the subject matter by Soltanali et al. (Soltanali et al. 2021). This study, like many others, proposed the implementation of the fuzzy theory to tackle the OEE uncertainties in measurements. For this study, the classical method is used, and imperfections will not be accounted for since it is not the focus of this analysis.

There is little to no statistical data on OEE in the literature that provides industry averages based on sector, but it is commonly agreed upon that a typical OEE ranges between 40 to 60%, with 85% being the ideal goal (Nakajima 1988).

There are many reasons behind low OEE values for equipment in manufacturing companies. The Six Big Losses is one way to categorize the causes of lost efficiency and it falls under the TPM umbrella. Equipment failure and setup and adjustments fall under availability losses. These losses include equipment breakdown, which would then need operator and/or maintenance intervention to recover the availability of the equipment. Setup and adjustments include change over times, recalibrating the machines, prepping the equipment at the beginning of the first shift, etc... Performance losses could be idling and minor stops, which is different than availability stops. The downtime caused by these reasons is often called "micro-downtime". This can include label roll change on a labeling machine for example, or changing the packaging material on any packaging equipment. They usually tend to be resolved by operators and do not need maintenance intervention, and are typically below 15 minutes (Zennaro et al. 2018). Reduced speed is simply running a machine at a lower speed than its maximum capability. Finally, quality losses occur when the product is defective and is rejected, therefore generating waste, both in time and material.

Many studies can be found in the literature that seek to find the principal cause behind OEE loss. For example, a case study on a beverage bottling company in Italy found that the main cause behind low OEE was Micro-downtime, accounting for 57% of the total loss in efficiency (Zennaro et al. 2018). Another study conducted in a cement factory showed that Reduced Speed Loss was the major contributor to low OEE (Muthalib et al. 2020). Table 1 below shows a summary of reviewed research in the literature with their respective methodologies and findings, covering the topics of OEE measurement, OEE improvement, and simulation models.

There are six papers that show the use of different methods to find the main causes behind OEE loss (Tsarouhas P. H. 2013; Rodrigues and Cabral 2017; Chundhoo et al. 2018; Tsarouhas P. 2019; Dewi et al. 2020; Muthalib et al. 2020). All of the causes fall under Availability and Performance loss, with some of them showing the significance of micro-downtime, which falls under Performance, and is another subset of the "minor stops" cause. Many of these studies do not explicitly show how the data was collected or recorded, and some fail to mention the shortcomings of the data collection methods, the accuracy of the OEE results, and whether studying a single machine can adequately represent an entire line.

Subsequently, two more papers were reviewed that cover the topic of OEE measurement (De Carlo et al. 2014; Pekarcíková et al. 2023). Comparing the traditional OEE measurement tools and simulation tools showed that the latter is a powerful tool that can represent the effectiveness of an entire line more accurately, although being a much more demanding tool in terms of data collection.

Additionally, three papers cover the topic of OEE improvements (Chundhoo et al. 2018; Fadhlurrahman et al. 2020; Garcia-Garcia et al. 2022). All of them used traditional OEE analysis for results and only one implemented a simulation model. These papers reinforce the use of TPM and lean manufacturing to improve effectiveness, as well as proving that determining the critical machine and resolving its losses can greatly improve the overall line performance.

During line commissioning and ramp-up, the reasons behind low OEE might be completely different. The Ramp-up period, as defined in the literature, starts right after product development is complete, and just before full-scale production is achieved (Terwiesch and E. Bohn 2001). A more accurate timeline for the ramp-up period would be the time between the first "wet run" on the line (as in, the first time bottles are filled with product) and the beginning of the plateau period where production is consistently achieving attainment. This definition of the ramp-up period will be used in this study.

3. Methods
Figure 1 showed the objectives and the means to attain them. In this section, the methods and tools used to reach these objectives will be discussed.

(1) Define the ramp-up period.
(2) Collect Data on attainment and downtime – VorneXL.
(3) Analyze the data to highlight major causes of inefficiency – diagrams, charts, reports.
(4) Perform Root Cause Analysis to attribute the inefficiencies to principles causes beyond the six big losses – Fishbone Diagram
(5) Perform Statistical Analysis on the two most critical machinery to understand failure patterns – MINITAB software.
(6) Perform risk analysis – Monte Carlo Simulation.
(7) Provide solutions and recommendations to improve line performance during ramp-up.

Data Analysis
In addition to the analysis performed by VorneXL, a more in-depth analysis will be performed to fill the gaps and provide insights. The software only provides data over a selected period of time and provide charts to visualize the results.

Statistical Analysis
MINITAB software will be used to determine the best fit for TTF and TTR data, as well as calculating the MTTF and comparing the results of the two machines. This will help determine the failure pattern of the most critical equipment behind most of the downtime on the line. The best probability distribution fit will be determined based on the AD index. These results will then be used in the risk analysis portion of this research.

Risk Analysis - Monte Carlo Simulation
To be able to reasonably predict whether a piece of machinery will cause a significant amount of downtime, a Monte Carlo simulation has to be run based on the probability distribution of the TTF and TTR data on the machines. To do that, MINITAB Workspace will be used for this simulation.

TTF, TTR, and Availability
Other important factors in this framework are the Time-to-Failure (TTF) and Time-to-Repair (TTR). They are used to determine the type of failure and how effective the maintenance practices at the facility are. In this paper, these factors are used to analyze the failure of the 2 most critical machines.

TTF is the time between two consecutive failures of an equipment, and TTR is the time it takes to repair the machine, or in other words, how long the machine was unavailable. The mean time-to-failure and the mean time-to-repair are powerful indicators of machine performance, and can be used to calculate the availability.

Goodness of Fit, Anderson-Darling Index in Statistical Analysis
A set of data can be attributed to a known probability distribution by performing what is called a Goodness of Fit test using statistical tools. Basically, we want to be able to predict the outcome of a certain set of data, in this case, the performance of certain equipment.

The Anderson-Darling Index was used for this analysis. This index measures the distance between the hypothesized function F, and the empirical data, F_n.

The best fit is the one which has the lowest "Distance" to the hypothesized function, hence the lowest AD Index. The confidence interval we want to use here is 95%, meaning that the p-value, which is the probability of getting a value at least as extreme as the null hypothesis, should be less than 0.05. In this case, the AD index is selected to determine the best fit.

Weibull and Lognormal Distributions

The Weibull distribution was introduced by Waloddi Weibull, a Swedish engineer, in 1937. It is frequently used in survival and reliability analysis (Clement and Lasky 2020). This 3-parameter Weibull distribution is characterized by 3 factors: the shape factor β, the scale factor, and the threshold factor. The shape parameter describes the distribution of the data, and can indicate the type of failure: infant-mortality, wear-out, or random.

Monte Carlo Simulation

The principle of Monte Carlo Simulation is basically to draw random samples from a set of data and observing the behavior, or plotting the behavior (Mooney 1997). This simulation helps managers and decision makers predict the outcome of a certain process where random variables may occur, and base decisions depending on their risk appetite, or aversion. There are many software applications developed to run Monte Carlo simulations, one of them is MINITAB Workspace.

4. Data Collection

The manufacturer has implemented a widely used production monitoring system called VorneXL. The software collects data from the equipment using sensors, and operators can scan downtime reasons using a handheld barcode scanner. The software then creates reports, diagrams, and insights from these inputs. The data for the new Mayo line will be based on this implementation.

The data collected on the equipment is a scanned reason, or a description of the problem, each with a corresponding date and time stamp, along with the duration of the downtime caused by this problem. These reasons are categorized based on the six big losses.

In addition, production data is collected for every finished product produced for each shift, which is by definition the attainment. The software shows the number of bottles produced and packed.

5. Results and Discussion

5.1 Numerical Results

Figure 2 below shows the variation of the attainment starting at the time the line first launched and over a period of 65 days (between May 29 and August 1st), which is 39 production days with actual data recorded. The ramp-up period should start at the official launch date, in this case May 29, and end at the time when production is hitting attainment consistently. According to the data, the ramp-up period could be roughly estimated as being between May 29 and July 13, ending when attainment reached beyond the target for five days.

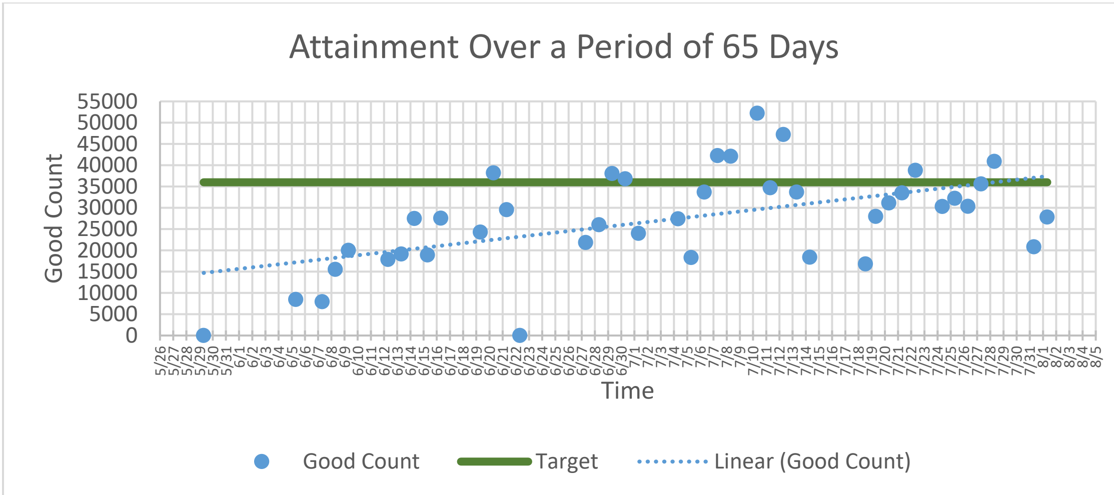

Figure 2. Attainment Over a Period of 65 Days

Table 1 below shows the downtime on the line per equipment. The Labeler and the Drop Packer are responsible for 67% of the downtime during the entire period. The downtime of the Labeler shown here also includes the downtime on the Steam Tunnel since they act as one system: if there is a missed sleeve on the Labeler, a jam-up will happen downstream in the steam tunnel.

Table 1. Contribution to Downtime per Machine

Machine	**Total Downtime (hrs)**	**Contribution**	**Machine State**
Labeler / Steam Tunnel	20.23	37%	New
Drop Packer / Case Former	16.46	30%	Old
Capper	7.56	14%	Existing, Fairly New
Checkweigher	5.91	11%	New
Filler	3.54	7%	Existing, Fairly New
Cap Sorter	0.40	1%	New
TOTAL	**54.10**		

TTF (time to failure) and TTR (time to repair) data are calculated and analyzed using Minitab software. A goodness of fit test was performed on both parameters and both machines. The TTF and TTR were not based on one single cause of downtime, but for total downtime per equipment. The data are shown in Table 2 and Table 3.

Based on the AD index (the lowest value), the best for the TTF data on the Labeler is a 3-Parameter Weibull distribution. On the other hand, the best fit on the TTF data for the Drop Packer is a Lognormal distribution shown chosen based on the lowest AD index.

Table 2. TTF Statistical Data for the Labeler and Drop Packer

	N	**N***	**Mean**	**StDev**	**Median**	**Minimum**	**Maximum**	**Skewness**	**Kurtosis**
Labeler/Steam Tunnel	695	0	61.8201	73.4323	33	0	450	2.24175	6.11202
Drop Packer	234	0	55.6838	72.9886	28	1	399	2.25033	5.38802

Table 3. TTR Statistical Data for the Labeler and Drop Packer

	N	N*	Mean	StDev	Median	Minimum	Maximum	Skewness	Kurtosis
Labeler/Steam Tunnel	232	0	3.73714	8.63706	1.59536	0.0336347	85.1783	7.24508	62.6549
Drop Packer	234	0	4.00769	6.85154	1.96303	0.0362225	56.0257	4.32882	22.8054

The β value (shape) for the 3-parameter Weibull is less than 1 (0.86789), which indicates that the failure for the Labeler is decreasing. This is typical for early-life failure. Also, this can indicate defective parts (defective mandrel in this case, or bad design). This type of failure pattern indicates infant mortality (Clement and Lasky 2020).

Also, calculating the MTTF for both machines based on their respective distributions, we get MTTF=61.82 minutes and MTTF=61.3 minutes for the Labeler and Drop Packer respectively. Table 4 and Table 5 show the MTTF values for both the Labeler and the Drop Packer as outputted by MINITAB.

Following a similar approach, it was found that the TTR for the Labeler and the Drop Packer follow a Lognormal distribution based on the AD index.

Table 4. TTF for the Labeler

		Standard	95% Normal CI	
Distribution	**Mean**	**Error**	**Lower**	**Upper**
Weibull	61.636	4.5965	53.2547	71.337
Lognormal	71.921	8.3189	57.3324	90.222
Exponential	61.888	4.0631	54.4154	70.387
Loglogistic	110.598	22.3895	74.3758	164.462
3-Parameter Weibull	61.817	4.8358	53.0298	72.060
3-Parameter Lognormal	69.448	8.0488	53.6722	85.223
2-Parameter Exponential	61.888	4.0148	54.4988	70.279
3-Parameter Loglogistic	131.625	37.8833	74.8772	231.379
Smallest Extreme Value	40.867	8.9538	23.3181	58.416
Normal	61.888	4.8147	52.4512	71.325
Logistic	48.979	3.8904	41.3541	56.604

Table 5. TTF for the Drop Packer

		Standard	95% Normal CI	
Distribution	**Mean**	**Error**	**Lower**	**Upper**
Weibull	55.042	4.3757	47.1002	64.322
Lognormal	61.296	7.1735	48.7323	77.099
Exponential	55.684	3.6402	48.9873	63.296
Loglogistic	94.27	20.3864	61.7014	144.029
3-Parameter Weibull	55.222	4.6159	46.8776	65.053
3-Parameter Lognormal	62.494	7.8477	48.8595	79.933
2-Parameter Exponential	55.684	3.5901	49.0737	63.184
3-Parameter Loglogistic	128.139	43.4822	65.8927	249.187
Smallest Extreme Value	36.6	8.654	19.638	53.561
Normal	55.042	4.3757	47.1002	64.322
Logistic	61.296	7.1735	48.7323	77.099

It is significant that the MTTF values for a new machine and an old, worn-down machine are comparable. One reason that might have contributed to this is the fact that in many cases, when the labeler breaks down, or misfires, issues arise downstream. A misfire at the labeler can cause fallen bottles to go through the steam tunnel. The bottles then jam up and stay inside the steam tunnel enough time for them to bloat and become misshapen. If the bottles continue downstream to the drop packer, they will jam up inside and cause another breakdown. In fact, bloated bottles are considered defective, and should be disposed of. Solving this problem meant resolving the bloated bottle issue, which was caused by the misfire at the labeler.

This could lead to the conclusion that the condition and performance of upstream equipment can affect the performance of the equipment downstream, regardless of their condition. Nevertheless, it would not be accurate to attribute the downtime on the drop packer entirely to issues with the labeler. A good practice in dealing with this type of issue is to analyze the line from the bottom up, because in this particular case, loose caps caused by issues on the capping machine might have driven the number of misfires at the labeler by a big margin.

5.2 Graphical Results

Figure 3 below shows the probability distribution as outputted by the software. There is 10.93% chance that the Labeler would not be available enough to produce the required attainment goal.

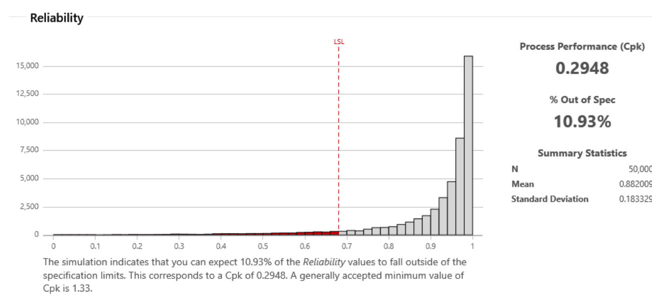

Figure 3. Availability Probability Distribution for the Labeler

Similarly, the same calculations were made for the drop packer, and this time the full 203 minutes are accounted for. Figure 4 below shows that the availability of the drop packer will be below 68% 15.21% of the time.

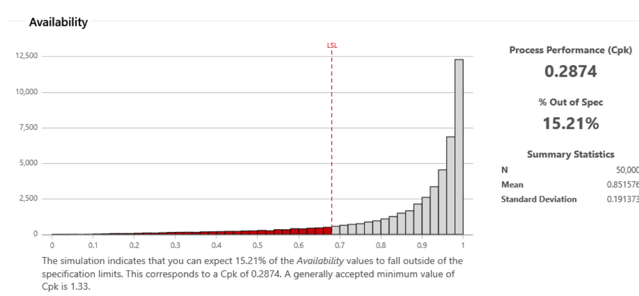

Figure 4. Availability Probability Distribution for the Drop Packer

5.3 Proposed Improvements

Before making the decision to bring a new piece of equipment without doing the FAT, a thorough risk analysis must be performed, as well as related losses in terms of possible line downtime and equipment shipment delay. Also, repurposing old machines should not only be limited to purchasing change parts for the new bottle format, but a machine audit and IO check (input/output, which is used to make sure the logic is working correctly) must be performed, possibly before even making the decision to use it on another line. This is because in certain cases, certain parts become obsolete, and the OEM does not support it anymore. Some parts could be redesigned by the OEM, simply because of bad historical performance, and would be recommended to be changed before using the machine again.

Although this study was done after the fact, it could be used as a reference or as framework to analyze a line before assembly and procurement. Old repurposed drop packing machines and new labelling machines are most likely to be the most problematic when running a unique bottle format.
When making decisions or machine selection, careful analysis must be made to reduce the ramp-up period duration. Short-term solutions and rushing the delivery of machinery is an aggressively high-risk method that would reduce the chances of achieving the production goal over a long period of time (in this case, at least 65 days).

6. Conclusion

Line performance during the ramp-up period can determine a product launch failure or success, and it is a critical period where all the equipment have to be brought up to speed to reach a steady output that can be reasonably maintained. It is quite different than line performance during normal operation and can point to issues in line design and shortcomings in the planning and commissioning processes of an organization.

A thorough risk analysis must be performed before making decisions related to new and old equipment, and this study showed that risk can be reasonably quantified based on historical data of the same type of machinery in the market.

The engineering management process in line design and commissioning is not straightforward but rather very complex where many contributing factors come into play. This places managers and designers under the constant pressure of handling uncertainty, but scientific approaches can help in quantifying it and reduce this potentially devastating aspect of all engineering projects.

References

Government of Canada, Sector: Food Processing Industry, Available: https://agriculture.canada.ca/en/sector/food-processing-industry/overview-food-beverage, September 12, 2023.

Chundhoo, V., Chattopadhyay, G., Gunawan, I. and Ibrahim, M. Y., OEE improvement of thermoforming machines through application of TPM, *Tibaldi australasia. IEEE International Conference on Industrial Engineering and Engineering Management*, 2018.

Clement, N., and Lasky, R., Weibull Distribution and Analysis: 2019, *2020 Pan Pacific Microelectronics Symposium*, pp. 1-5, 2020.

De Carlo, F., Arleo, M. and Tucci, M., OEE evaluation of a paced assembly line through different calculation and simulation methods: A case study in the pharmaceutical environment, *International Journal of Engineering Business Management*, vol. 6, no. 1, 2014.

Devonshire, J., Evocon: OEE Fundamentals, Available: https://evocon.com/articles/world-class-oee-industry-benchmarks-from-more-than-50-countries/, August 16, 2022.

Dewi, S., Alhilman, J. and Atmaji, F. T., Evaluation of Effectiveness and Cost of Machine Losses using Overall Equipment Effectiveness (OEE) and Overall Equipment Cost Loss (OECL) Methods, a case study on Toshiba CNC Machine, *IOP Conference Series: Materials Science and Engineering*, vol. 847, 2020.

Fadhlurrahman, Z., Yuniaristanto, Hisjam, M. and Zakaria, R., Supply Chain Performance Analysis Using Hybrid Overall Equipment Effectiveness and Discrete Event Simulation (Case Study: Futura Energy Nusantara), *IOP Conference Series: Materials Science and Engineering*, vol. 943, no. 1, 2020.

Garcia-Garcia, G., Singh, Y. and Jagtap, S., Optimising Changeover through Lean-Manufacturing Principles: A Case Study in a Food Factory, *Sustainability*, vol. 14, no. 14, 2022.

Lintilä, J., and Takala, J., Reducing time losses in operational actions of a food production lines, *Management and Production Engineering Review*, vol. 4, no. 2, pp. 78-88, 2013.

Luozzo, S., Pop, G. and Schiraldi, M., The human performance impact on oee in the adoption of new production technologies, *Applied Sciences*, vol. 11, no. 18, 2021.

Mooney, C. Z., *Monte Carlo Simulation*, SAGE Publications, Inc., 1997.

Muchiri, P. and Pintelon, L., Performance measurement using overall equipment effectiveness (OEE): Literature review and practical application discussion, *International Journal of Production Research*, vol.46, no. 13, pp. 965-995, 2008.

Muthalib, I. S., Rusman, M. and Griseldis, G. L., Overall Equipment Effectiveness (OEE) analysis and Failure Mode and Effect Analysis (FMEA) on Packer Machines for minimizing the Six Big Losses-A cement industry case, *IOP Conference Series: Materials Science and Engineering*, vol. 885, no. 1, 2020.
Nakajima, S., *Introduction to TPM: Total Productive Maintenance*, 11th edition, Productivity Pr, 1988.
Pekarcíková, M., Trebuna, P., Kliment, M., Trojan, J., Kopec, J., Dic, M. and Kronová, J., Case Study: Testing the Overall Efficiency of Equipment in the Production Process in TX Plant Simulation Software, *Management and Production Engineering Review,* vol. 14, no.1, pp. 34-42, 2023.
Rodrigues, J. B. and Cabral, A. C., Use of packing equipment efficiency as an estimate of the overall plant effectiveness and as a tool to improve financial results of a food-processing unit, *Brazilian Journal of Food Technology*, vol. 20, no. 0, 2017.
Soltanali, H., Khojastehpour, M. and Torres Farinha, J., Measuring the production performance indicators for food processing industry, *Measurement: Journal of the International Measurement Confederation*, vol. 173, 2021.
Terwiesch, C. and E. Bohn, R., Learning and process improvement during production ramp-up, *International Journal of Production Economics*, vol. 70, no. 1, 2001.
The SQF Institute, SQF Food Safety Code for Manufacturing Edition 8, *Food Marketing Institute (FMI)*, 2017.
Tsarouhas, P., Improving operation of the croissant production line through overall equipment effectiveness (OEE): A case study, *International Journal of Productivity and Performance Management*, vol. 68, no. 1, 2019.
Tsarouhas, P. H., Equipment performance evaluation in a production plant of traditional Italian cheese, *International Journal of Production Research*, vol. 51, no. 19, 2013.
Wunsch, N.-G., Consumer Goods and FMCG: Food and Nutrition. Available: https://www.statista.com/topics/5140/food-processing-in-canada/?gclid=Cj0KCQjwnf-kBhCnARIsAFlg491A8o3sBQDnxeHGDfCW3LuBlgKTpdr1H-v6OkeyWipoYV8KNeGGZTsaAuEpEALw_wcB#topicOverview, Juley 08, 2021.
Zennaro, I., Battini, D., Sgarbossa, F., Persona, A. and De Marchi, R., Micro downtime: Data collection, analysis and impact on OEE in bottling lines the San Benedetto case study, *International Journal of Quality and Reliability Management*, vol. 35, no.4, 2018.

Biographies

Dr. Dima Jawad is an Associate Professor in the Department of Mechanical and Manufacturing Engineering at Ontario Tech University in Ontario. Dr. Jawad has a Ph.D. degree in Civil Engineering (transportation) and master's degree in urban planning and development from Rutgers University, New Jersey, USA. Dr. Jawad has more than 10 years of experience in graduate and undergraduate teaching and academic research. Her area of research covers transportation engineering and planning, economic and multi-criteria evaluation of transportation and infrastructure projects, sustainable systems. She also has several years of industry experience in post-war rehabilitation and reconstruction of cities in Lebanon where she has worked as a consultant for the public sector as well as the World Bank projects via the Council of Development and Reconstruction in Lebanon. Dr. Jawad is a member of the Lebanese Order of Engineers, the American Society of Civil Engineers

Peter El Khoury has a master's degree in Engineering Management from Ontario Tech University, Ontario, Canada. He earned is B.E. in Civil Engineering at Notre Dame University (Louaize) in Lebanon. He has co-authored a paper published in the City Street 4 Conference about transit-oriented development in the aftermath of a civil war. He also has professional experience working as a junior structural engineer designing precast elements, post-tension slabs, and reinforced concrete slabs, and is currently working in a food manufacturing company in the engineering department, where he performs plant layout design, process design, and procurement and commissioning of new equipment.