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Machine Failure Analysis Using Multinomial Logistic Regression

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ABSTRACT

Purpose: The main purpose of this study is to carry out a failure analysis of a filling machine by applying multinomial logistic regression.

Design/methodology/approach: For this purpose, data related to failure mode, product, scrap rate, and shift parameters were collected from the machine and analysis was conducted by establishing two multinomial logistic regression models.

Findings: Statistical results suggest that a hydraulic failure must be expected while filling the mix product. Besides, it is highly probable that a final folder failure will occur while filling the cherry product. Paper failure stands out while filling the apple product compared to other products. In addition, it is likely that a final folder failure will occur while filling this product. Photocell failure is common while filling the peach product. Results of the study show that the odd for low-level scrap is high when there is any failure in the machine.

Discussion: A more effective analysis can be performed by collecting parameters that may affect the position of machinery such as vibration, humidity, temperature and pressure through the sensors to be installed on various units of the filling machine and adding them into the models developed under the study.

1. Introduction

Machines constitute one of the most important resources in manufacturing. Machine failures are inevitable due to unexpected variations in manufacturing processes (Chiu et al., 2020) and, along with faulty production, affect the efficiency of a manufacturing process (Borucka and Grzelak, 2019). In addition, machine failures can cause large production losses by creating many negative consequences (Xia et al., 2013). Therefore, machine failure analysis (MFA) is a critical process for understanding the problems that cause a machine to fail. As machine use and age increase in manufacturing systems, the recurrence of machine failures increases (Zhang et al., 2014; Kim and Makis, 2009). MFA should be performed to better understand the causes of these repeated failures.

When a machine stops, it takes time to get it repaired. In addition, machine failures can create scraps and cause an increase in faulty products (Lin and Chang, 2012). For these reasons, machine failures affect the capacity of a manufacturing system. Additionally, each time a machine stops, a cost is generated. With an effective MFA, the most appropriate measures can be taken to prevent the recurrence of machine failures by getting to the root causes of failure (Affonso, 2006). Moreover, when a failure occurs, the raw material, semi-product, or product processed in the machine may be damaged. As a result, these items are either rework or directly scrapped if they cannot be processed (Chiu et al., 2010). In both cases, the production rate decreases and costs increase (Liberopoulos et al., 2007; Chiu et al., 2013). Therefore, the increase in scrap rates affects the performance of the manufacturing process (Hilmola and Gupta, 2015). The decrease in machine-sourced scrap rates to be achieved as a result of MFA, both increases customer satisfaction by improving quality and has a serious impact on profitability (Molnar, 2017).

MFA is vital to reduce machine breakdown and increase uptime. Understanding the effect of machine failures is critical for improving machine performance and reliability (Mourani et al., 2007). Also, understanding the behavior of different failure modes of a machine is the basis for effective preventive maintenance planning (Smadi and Kamrani, 2011). Machine failures are closely related to profitability, quality, reliability,

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maintainability, and safety efforts in manufacturing processes. Therefore, MFA helps considerably in improving the reliability and safety of a machine.

A machine can fail for a variety of reasons. However, it may not always be possible to clearly determine the causes of failure modes due to variations in manufacturing. For this reason, analysis of the relationship between the failure modes and the parameters that may affect the failure modes is essential. Thus, the probability of failure modes to occur can be determined according to various parameters. In addition, scrap rates constitute another important issue resulting from machine failures. As in failure mode analysis, manufacturing parameters related to scrap rates should be determined and the effect of these parameters on scrap rates should be analyzed. As a result of the analysis, the likelihood of scrap rates can be determined, and effective measures can be taken.

This study focuses on the failure analysis of machinery, one of the most important resources of manufacturing enterprises. Analyses on the reasons for machine failures resulting in the interruption of machinery and the probability thereof can allow for more effective predictive maintenance activities regarding the machinery. Besides, the scrap quantities caused by the interruption of machinery directly affect production costs and capacity. Briefly, the analytic models presented in this study aim to be a guide for increased efficiency and cost-oriented operation for manufacturing enterprises running intensively based on machinery. In this study, MFA was performed on a 1-liter juice filling machine by using the multinomial logistic regression method. For this purpose, two multinomial logistic regression models were generated. In the first model, the aim was to perform failure mode analysis. In this regard, the relationship of product and shift variables with failure modes was investigated. The purpose of the second model was scrap analysis. For this purpose, the relationship of failure mode, product, and shift variables with scrap numbers was analyzed. The remainder of the work is organized as follows: In the second section, a literature review defining machine failure analysis is presented; an explanation of multinomial logistic regression, which is the analysis method of this study, is provided in the third section; the fourth explains the structure of the filling machine, the data collection process, and the variables of the established models; the fifth section addresses the statistical results of the two established models and the failure analysis; and finally, the results of the study are presented in the sixth section.

2. Machine Failure Analysis And Literature Review

Blanke et al., (2006) state that a failure describes the inability of a system or a component to accomplish its function. Failures not only affect the expected performance of a machine, but also cause many economic losses. Blischke and Murthy (2003) classified machine failures as mechanical, electrical, thermal, radiation failures, chemical, or combinations of two or more of these. In manufacturing systems, machine failures constitute the fundamental cause of many problems such as decrease in availability, decrease in reliability, increase in repair times, prolongation of delivery times, decrease in capacity, decrease in customer satisfaction, decrease in productivity, rescheduling, decrease in quality, decrease in production rate, increase in scrap and rework, and increase in cost (Guo and Nonaka, 1999; Al-Hinai and ElMekkawy, 2011; Das et al., 2011; Nodem et al., 2011; Glock, 2013).

MFA serves for the determination of existing and potential failure modes of a machine's components and the actual and potential causes and effects of these modes (Bloch and Geitner, 2012; Scutti and McBrine, 2002). Machine failures cannot be completely avoided, yet their effects and risks can be determined through MFA. MFA enables the development of correct action plans to reduce or eliminate the possible effects of existing and potential failures (Stamatis, 2019) as its main objectives include improving machine reliability, reducing maintenance costs, reducing accident risks, increasing customer satisfaction, and improving product quality (Affonso, 2006).

Failure modes are associated with the machine itself, its components, and operating conditions. In order to prevent future machine failures, MFA can be used to examine the effect of all parameters directly or indirectly related to failure modes on failure modes. Effective preventive actions can thus be taken by identifying such bottleneck points. In addition, one of the crucial factors affecting production efficiency and production costs is scrap rates (Shakibania et al., 2022; Kumar et al., 2009). Within the MFA, the factors affecting the scrap rate should also be analyzed.

MFA is not possible without availability of data on repeated machine failures. For this reason, first all data regarding downtime such as those related to the machine's failure modes, product, shift, scrap amounts, temperature, humidity, and vibration should be collected. Afterwards, MFA can be performed using the obtained historical data.

Smadi and Kamrani (2011) statistically modeled failure and repair behavior of a machine through distribution fitting for MFA. Ragab et al. (2019) performed a multiple failure modes analysis in rotating machines based on a supervised machine learning approach called logical analysis of data and a set of non-parametric cumulative incidence of functions. Ahmad et al. (2012) studied a failure analysis of machine components by integrating the failure mode effect and criticality analysis and failure time modelling based on proportional hazard model. Yang et al. (2010) proposed a fuzzy failure mode and effects analysis model integrating the fuzzy linguistic scale method for a CNC lathe. Lo et al. (2019) developed a novel failure mode and effect analysis model based on multi-criteria group decision-making using rough best–worst method with a modified rough TOPSIS technique for machine tool risk analysis. Sheng et al. (2016) proposed the improved failure mode and effect analysis based on the gray correlation theory for CNC boring machine tools. Janak et al. (2016) conducted failure modes and effects analyses and applied diagnostics extension methods on a machine tool spindle. Jin et al. (2017) presented a modified failure mode and effects analysis based on set pair analysis for CNC machine tools. Wang et al. (2001) carried out an early failure mode and effects analysis with reliability analysis for machining centers. Du et al. (2017) conducted failure mode, effects, and criticality analysis of a remanufactured gear hobbing machine using the risk priority number method. Gupta and Mishra (2017) studied a failure mode effect and criticality analysis using fuzzy logic for a conventional milling machine. In addition, there are various scrap rate focused studies in the literature using different methods (Liberopoulos et al., 2007; Molnar, 2017; Shakibania et al., 2021; Kumar et al., 2009). As presented above, several studies on machine failures using various methods can be found in the literature. However, although there are many studies on machine failures using logistic regression, studies utilizing multinomial logistic regression are rather rare (Pramesti et al., 2016; Caesarendra et al., 2010; Kozlowski et al., 2019; Yan et al., 2004, Yang and Lee, 2005, Wu et al., 2017).

3. Multinomial Logistic Regression

Logistic regression is one of the common methods used to analyze the relationship between dependent and independent variables in cases where the dependent variable is discrete such as binary, categorical, and ordinal, and the independent variables are metric or nonmetric variables (Torres et al., 2009; Hair et al., 2014). Logistic regression is a flexible method since the variables in the model do not need to be in a specific form of distribution (Tabatchnick and Fidell, 2019). In addition, the logistic model is widely used because it estimates the probability as a value between 0 and 1 (Kleinbaum and Klein, 2010). With the linear regression equation $Y = \beta_0 + \beta_1 X_1 \ldots + \beta_k X_k$, where Y is the dependent variable, β_0 is the intercept, β_1 is the slope coefficient for the independent variable X_1, and β_k is the slope coefficient for the kth independent variable, a logistic model can be defined as follows to calculate the odds for the dependent variable, where P is the probability of the dependent variable Y and the sum of $\beta_i X_i$ for *i* ranging from 1 to *k*.

$$P(Y) = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^{k} \beta_i X_i)}} \qquad (1)$$

Multinomial logistic regression (MLR) is a type of logistic regression used when the dependent variable has at least three categories or is ordinal (Agresti, 2007). One of the categories of the categorical variables in MLR is determined as a reference category and the analysis is carried out accordingly. By using the odds value, the likelihood of each category of a variable is compared with the reference category of that variable and the analysis is performed accordingly. If 0 is the reference category in an MLR model with 0, 1, and 2 categories as the dependent variable, two logistic models consisting of 1 and 0 as well as 2 and 0 are obtained for comparison in addition to odds values (Hosmer et al., 2013). Odds is a measure of the probability of an event to occur. An odds ratio, on the other hand, is the ratio of the likelihood of an event as the one below (p) to the probability that this event will not occur (Field, 2009).

$$Odds\ ratio = \frac{p}{1-p} \tag{2}$$

Accordingly, the logit model can be expressed as follows using the logistic transformation with 1 and 2 equations.

$$Logit\ P(Y) = ln\left[\frac{P(Y)}{1-P(Y)}\right] = ln\left[e^{(\beta_0 + \sum_{i=1}^{k}\beta_i X_i}\right] = \beta_0 + \sum_{i=1}^{k}\beta_i X_i \tag{3}$$

The logit value is negative if the odds value is less than 1, and positive if it is larger. If this ratio is above 1, it indicates that the independent variable has a positive effect on the dependent variable, i.e., a positive relationship, and that if it is less than 1, the independent variable has a negative effect on the dependent variable. Odds ratio allows easy interpretation of the results in an MLR model (Sluis and Giovanni, 2016). An MLR model consisting of 3 categories (0, 1, 2) with a reference category of 0 and one independent variable, can be expressed as follows, where X_1 is the independent variable (Kleinbaum and Klein, 2010).

$$\ln\frac{P(Y=1\|X_1)}{P(Y=0\|X_1)} = \beta_{1+}\beta_{11}X_1 \tag{4}$$

$$\ln\frac{P(Y=2\|X_1)}{P(Y=0\|X_1)} = \beta_{2+}\beta_{21}X_1 \tag{5}$$

MLR is a method that has attracted a great deal of attention in various fields in the literature, such as supply chain management (Ma et al., 2020, Sluis and Giovanni, 2016), manufacturing (Meidan et al., 2011), marketing (Gordon et al., 2018), finance (Kim et al., 2016; Luo et al., 2016), research and development (Rodgers et al., 2019), management and organization (Giritli et al., 2013), medicine (Ke et al., 2016), maritime research (Rong et al., 2022), topography (Chan et al., 2019), and livestock (Torres et al., 2009).

4. Data Collection And Variables

The present study was conducted on a filling machine, which is the first station in a production line that fills 1-liter containers with fruit juice. After the juice itself is produced on a separate line, it comes to the filling machine, which is the beginning of the container production line. Here, a box is made from cardboard in the form of a coil, filled with fruit juice, purged with nitrogen, closed without a lid, and sent to the printer, which is the next operational line. The filling machine, as shown in Figure 1, consists of seven basic units: the automatic splicing unit, aseptic room, jaw system, motion unit, final folder, electrical cabinet, and service unit. In the automatic splicing unit, automatic switching from one paper bobbin to another occurs after the paper bobbin used to make boxes is finished. This unit is used for non-stop production of the filling machine. The area where the juice box is sterilized is the aseptic or peroxide bath unit. Here, the box is sterilized with peroxide and purged with nitrogen gas. Within the jaw system, the cutting and sticking operations that create the box are performed. The motion unit contains the motors that drive all the motions of the filling machine. The last folder unit is the section where the folding processes of the boxes take place. Here, the parts on the two sides of the boxes, called ears, are glued. The electrical cabinet is where all the electrical components of the filling machine are located. The service unit, on the other hand, is the unit where the water of the filling machine working with air and water is cooled and the air pressure is adjusted.

Fig 1. Fruit juice filling machine

The main purpose of this study was to analyze the failure of this filling machine. For this reason, 6-months of failure modes, scrap amounts, product, and shift data related to the machine were obtained. There are nine types of failure modes in the filling machine: final folder, paper, photocell, hydraulic, strip, service unit, electrical, nitrogen, and peroxide. From among the obtained failure modes, strip, service unit, electrical, nitrogen, and peroxide, all had the lowest frequencies and were thus excluded from the analysis. As a result, only the final folder, paper, photocell, and hydraulic failure modes were analyzed.

Final folder failure occurs due to situations such as the jamming and rotation of the boxes in the unit because of the breakdown of the transfer belt, printing unit, pulldown, or pressure device mechanisms in the final folder unit. Photocell failure is caused by the fact that the barcode on the boxes in the jaw unit is not read by the photocells inside the machine. Hydraulic failure occurs while the gluing and closing operations are performed to close the box by the hydraulic system located in the jaw unit. If failure occurs at this point, the box does not close correctly, leading to downtime. In the event of a paper failure, when a paper bobbin runs out in the automatic splicing unit and passes to the other bobbin, it may stick to the other. In addition, paper breakage in the bobbins is also a cause of paper failures.

Each time a failure occurs, the machine stops and the boxes inside the machine are evaluated as scrap. It is not possible to rework these boxes. Three categories of scrap data were generated by the production engineers: 1-30 pieces (low), 31-40 pieces (medium) and 41-150 pieces (high). This machine facilitates the filling of 11 different fruit juices. However, fruit juice varieties with low frequency were excluded and 4 types of fruit juice (mixed, cherry, apple, and peach) were included in the analysis. The machine works in three shifts: 24:00-08:00 (shift 1), 08:00-16:00 (shift 2) and 16:00-24:00 (shift 3). Overall, 299 failures were analyzed using the 6-month data from the machine.

5. Machine Failure Analysis

In this study, two MLR models were established for MFA. In the first model, product and shift were determined to be the independent variables, and failure modes were the dependent variables. The aim of this model was to examine the relationship of products and shifts with failure modes. In the second model, scrap amounts constituted the dependent variable and product, failure modes, and shift variables were the independent variables. The purpose of this model was to analyze the effect of the independent variables on scrap amounts. SPSS statistical software was used for analysis in this study. Statistical analyses of the established models were performed with a 95% confidence interval. Analysis results were evaluated together for both models.

5.1. Model Fit

Model fit is utilized with the log-likelihood function to compare the observed values with the values predicted in the MLR (Hosmer et al., 2013). The odd ratio test is one of the most widely used methods for model fit in MLR (Petrucci, 2009). The chi-square test for statistical significance is used to evaluate the reduction in the log-likelihood value (Hair et al., 2014). -2 Log Likelihood values were computed at 274.725 for Model 1 and 286.26

for Model 2 without any independent variables and 146.237 for the final Model 1 and 215.12 for the final Model 2 with all independent variables. The number of unexplained variables decreased in both models. This change was significant, meaning that both final models explained a significant amount of the original variability (Field, 2009). In addition, the odd ratio test statistics of both models are as follows:

χ^2 (15) = 128.488, significance p- value (0.000) < 0.05 for Model 1
χ^2 (71.1) = 215.117, significance p- value (0.000) < 0.05 for Model 2

These results demonstrate that both models were statistically significant.

5.2. Effect Size

Pseudo R-Square is used to measure the overall effect size of the model in MLR (Garson, 2014). R-Square measures the explanatory power of the model, that is, the effect of independent variables on dependent variables. R-Square shows how well the independent variables explain the dependent variable (Hu et al., 2006). The larger the value, the better the variables are at explaining the model. However, R-Square values in logistic regression tend to be smaller than R-Square values in linear regression (Petrucci, 2009). The SPSS package program provides Cox and Snell as well as Nagelkerke and McFadden R-Square statistics to analyze the effect size of the model. According to Nagelkerke statistics, 37% of the variation in the dependent variable could be explained by the independent variables in Model 1. For Model 2, the Nagelkerke value was 0.24. It can be said that, unlike linear regression, R-Square is not a useful statistic due to the assumptions of MLR.

5.3. Odd Ratio Test

This statistic tests whether independent variables have a significant effect on a model (Tabatchnick and Fidell, 2018). The p value of the independent variables being less than 0.05 indicates that these variables are statistically significant. In other words, the contribution of the independent variables to the model is sufficient. Table 1 shows the contribution of each variable to Model 1 and Model 2. Since the p values of both product and shift independent variables were less than 0.05 for Model 1, the contribution of both variables to the model was sufficient. For Model 2, on the other hand, since the p values of the independent variables of failure mode, product, and shift were less than 0.05, the relationship between the independent variables and the dependent variables is statistically sufficient.

Table 1. Odd Ratio Test for Model 1 and Model 2

Odd Ratio Tests for Model 1					**Odd Ratio Tests for Model 2**				
Effect	**-2 Log Likelihood of Reduced Model**	**Chi-Square**	**df**	**Sig.**	**Effect**	**-2 Log Likelihood of Reduced Model**	**Chi-Square**	**df**	**Sig.**
Intercept	146.237	0	0	.	**Intercept**	215.117	0	0	.
product	247.543	101.31	9	0.000	**failuremode**	253.451	38.33	6	0.000
shift	169.2	22.962	6	0.001	**product**	229.78	14.66	6	0.023
					shift	238.856	23.74	4	0.000

5.4. Parameter Estimates

Odd ratio tests do not indicate to what extent the independent variables affect the model. For this reason, parameter estimation should be carried out for the relationship between the significant independent variables and the dependent variable. In this regard, the odds ratio is one of the criteria used to evaluate the effect size of the estimators (Tabatchnick and Fidell, 2018). In order to make comparisons in MLR, one of the categorical variables is selected as the reference category. The j-1 odds ratio is calculated for as many as j-1 variables from the dependent variables within the J category. With the variable in the reference category, the odds ratio shows how many times more or how many times less the probability of observation is for one variable than the other one (Garson, 2014). Parameter estimations were made by taking the categories of dependent variables in the models separately as reference categories. In the resulting statistics, from among the independent variables, the values of the categories that were statistically significant ($p < 0.05$) were shown and interpreted. The Exp(B) value of each parameter in the tables represents the odds ratio.

5.4.1. Parameter Estimates And Odds Ratios for Model 1

In order to analyze each failure mode for Model 1, parameter estimate tables were created on the basis of failure mode. Table 2 presents the parameter estimates and odds ratios for Model 1 based on paper failure mode. As the odds ratio of mixed and cherry products was below 1, as shown in the table, it had a negative effect on the paper failure mode. Therefore, compared to mixed and cherry, the probability of paper failure in peach (the reference category) juice filling was approximately 3.5 (1/0.283) and 5.8 (1/0.173) times higher than final folder failure, respectively. Compared to shift 3, the probability of paper failure occurring in shift 1 was approximately 3.7 times greater than the final folder failure. Compared to peach juice, the probability of paper failure in cherry juice and apple juice filling was approximately 30 and 24 times higher than hydraulic failure, respectively. In addition, compared to peach juice, the probability of paper failure in apple juice filling was approximately 3.2 times greater than photocell failure. In addition, the probability of paper failure occurring in shift 1 than in shift 3 was approximately 2.2 times higher than photocell failure.

Table 2. Parameter Estimates And Odds Ratios for Model 1(Paper)

The reference category: Final folder							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Paper	Intercept	0.441	0.536	0.679	1	0.410	
	[product=Mixed]	-1.263	0.586	4.647	1	0.031	0.283
	[product=Cherry]	-1.755	0.569	9.516	1	0.002	0.173
	[product=Peach]	0[b]			0		
	[shift=1]	1.299	0.447	8.455	1	0.004	3.664
	[shift=3]	0[b]			0		
The reference category: Hydraulic							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Paper	Intercept	-0.772	0.451	2.933	1	0.087	
	[product=Cherry]	3.403	1.087	9.806	1	0.002	30.065
	[product=Apple]	3.166	0.806	15.434	1	0.000	23.712
	[product=Peach]	0[b]			0		
The reference category: Photocell							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Paper	Intercept	-0.912	0.432	4.460	1	0.035	
	[product=Apple]	1.166	0.463	6.350	1	0.012	3.209
	[product=Peach]	0[b]			0		
	[shift=1]	0.805	0.456	3.120	1	0.077	2.237
	[shift=3]	0[b]			0		

Table 3 indicates that, compared to mixed, cherry, and apple juice, the probability of photocell failure in peach juice filling, which is the reference category of the product independent variable, was approximately 9.9 (1/0.101), 9.01 (1/0.111), and 6.9 (1/0.146) times higher, respectively, than final folder failure. Likewise, compared to apple juice, which had a negative effect on photocell failure, the probability of photocell failure in peach juice filling was approximately 3.2 (1/0.312) times more than paper failure. Compared to shift 1, in shift 3, which is the reference category of shift independent variable, the probability of photocell failure was approximately 3.5 (1/0.447) times greater than paper failure. In addition, statistical results show that, compared to peach fruit juice, the probability of photocell failure in cherry juice and apple juice filling was approximately 19.3 and 7.4 times higher, respectively, than hydraulic failure. Moreover, compared to mixed fruit juice, the probability of photocell failure in filling of peach fruit juice, which is the reference category, was approximately 3.5 (1/0.290) times greater than hydraulic failure.

Table 3. Parameter Estimates and Odds Ratios for Model 1(Photocell)

The reference category: Final folder							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Photocell	Intercept	1.354	0.489	7.668	1	0.006	
	[product=Mixed]	-2.293	0.587	15.249	1	0.000	0.101
	[product=Cherry]	-2.199	0.523	17.688	1	0.000	0.111
	[product=Apple]	-1.925	0.528	13.306	1	0.000	0.146
	[product=Peach]	0^b			0		
The reference category: Paper							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Photocell	Intercept	0.912	0.432	4.460	1	0.035	
	[product=Apple]	1.166	0.463	6.350	1	0.012	0.312
	[product=Peach]	0^b			0		
	[shift=1]	-0.805	0.456	3.120	1	0.077	0.447
	[shift=3]	0^b			0		
The reference category: Hydraulic							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Photocell	Intercept	0.140	0.388	0.130	1	0.719	
	[product=Mixed]	-1.239	0.474	6.840	1	0.009	0.290
	[product=Cherry]	2.959	1.074	7.596	1	0.006	19.287
	[product=Apple]	2.000	0.803	6.199	1	0.013	7.388
	[product=Peach]	0^b			0		

As seen in Table 4, compared to peach fruit juice, the probability of final folder failure in mixed fruit juice and cherry juice filling was approximately 3.5 and 5.8 times higher, respectively, than paper failure. The probability of final folder failure occurring in shift 3 was approximately 3.66 (1/0.273) times higher than in shift 1, which had a negative impact on final folder failure. Compared to peach juice, the probability of final folder failure in mixed juice, cherry juice, and apple juice filling was approximately 9.9, 9, and 6.9 times greater, respectively, than photocell failure. Moreover, compared to peach juice, the probability of final folder failure in mixed juice, cherry juice, and apple juice filling was approximately 2.9, 174, and 50.6 times higher, respectively, than hydraulic failure. Finally, compared to shift 1, in shift 3, which is the reference category of shift independent variable, the probability of final folder failure was approximately 3.47 (1/ 0.287) times greater than hydraulic failure.

Table 4. Parameter Estimates and Odds Ratios for Model 1 (Final Folder)

The reference category: Paper							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Final folder	Intercept	0.441	0.536	0.679	1	0.410	
	[product=Mixed]	1.263	0.586	4.647	1	0.031	3.537
	[product=Cherry]	1.755	0.569	9.516	1	0.002	5.786
	[product=Peach]	0^b			0		
	[shift=1]	-1.299	0.447	8.455	1	0.004	0.273
	[shift=3]	0^b			0		
The reference category: Photocell							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Final folder	Intercept	-1.354	0.489	7.668	1	0.006	
	[product=Mixed]	2.293	0.587	15.249	1	0.000	9.903
	[product=Cherry]	2.199	0.523	17.688	1	0.000	9.019
	[product=Apple]	1.925	0.528	13.306	1	0.000	6.852
	[product=Peach]	0^b			0		
The reference category: Hydraulic							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Final folder	Intercept	-1.214	0.511	5.641	1	0.018	
	[product=Mixed]	1.054	0.525	4.025	1	0.045	2.869
	[product=Cherry]	5.159	1.114	21.444	1	0.000	173.947
	[product=Apple]	3.925	0.854	21.098	1	0.000	50.628
	[product=Peach]	0^b			0		
	[shift=1]	-1.247	0.477	6.836	1	0.009	0.287
	[shift=3]	0^b			0		

As indicated in Table 5, the probability of hydraulic failure in peach juice filling, which is the reference category of the product independent variable, was approximately 2.9 (1/0.349), 174 (1/0.006), and 50.6 (1/0.006) times greater, respectively, than mixed juice, cherry juice, and apple juice, which had negative effects on hydraulic failure. However, the probability of hydraulic failure in the 1st shift compared to the 3rd shift was 3.5 times higher than photocell failure. In addition, compared to cherry and apple juice, the probability of hydraulic failure in peach fruit juice filling, which is the reference category, was approximately 30 (1/0.033) and 23.7 (1/0.042) times more, respectively, than paper failure. Moreover, compared to peach fruit juice, the probability of hydraulic failure in mixed fruit juice filling was 3.4 times greater than photocell failure. Furthermore, compared to cherry and apple juice, which have negative effects on hydraulic failure, the probability of hydraulic failure in peach juice filling was approximately 19.2 (1/0.052) and 7.4 (1/0.042) times higher, respectively, than photocell failure.

Table 5. Parameter Estimates and Odds Ratios for Model 1 (Hydraulic)

The reference category: Final folder							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Hydraulic	Intercept	1.214	0.511	5.641	1	0.018	
	[Product=Mixed]	-1.054	0.525	4.025	1	0.045	0.349
	[Product=Cherry]	-5.159	1.114	21.444	1	0.000	0.006
	[Product=Apple]	-3.925	0.854	21.098	1	0.000	0.020
	[Product=Peach]	0[b]			0		
	[Shift=1]	1.247	0.477	6.836	1	0.009	3.480
	[Shift=3]	0[b]			0		
The reference category: Paper							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Hydraulic	Intercept	0.772	0.451	2.933	1	0.087	
	[Product=Cherry]	-3.403	1.087	9.806	1	0.002	0.033
	[Product=Apple]	-3.166	0.806	15.434	1	0.000	0.042
	[Product=Peach]	0[b]			0		
The reference category: Photocell							
Failure mode		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
Hydraulic	Intercept	-0.140	0.388	0.130	1	0.719	
	[Product=Mixed]	1.239	0.474	6.840	1	0.009	3.451
	[Product=Cherry]	-2.959	1.074	7.596	1	0.006	0.052
	[Product=Apple]	-2.000	0.803	6.199	1	0.013	0.135
	[Product=Peach]	0[b]			0		

The three MLR models for which final folder failure mode was used as the reference category for Model 1 are:

$$Y_{paper} = 0.441 - 1.263X_{mix} - 1.755X_{cherry} - 0.759X_{apple} + 1.299X_{shift1} - 0.140X_{shift2}$$

$$Y_{photocell} = 1.354 - 2.293X_{mix} - 2.199X_{cherry} - 1.925X_{apple} + 0.493X_{shift1} - 0.188X_{shift2}$$

$$Y_{hydraulic} = 1.214 - 1.054X_{mix} - 5.159X_{cherry} - 3.925X_{apple} + 1.247X_{shift1} - 0.574X_{shift2}$$

Table 6 shows the probability of failure mode occurrence when filling each product on a shift basis, which is calculated by using Equation 1 with these MLR models. The cells with the highest probability are highlighted in the table, and those with a probability of over 50% are marked in bold. Considering the highest probability ratios, it is seen that there was a 56% and 39% probability of hydraulic failure in shift 1 and shift 3, respectively, and a final folder failure with a 42% probability in shift 2, when filling the mixed product. The probability of final folder and paper failures in shift 1 in cherry product filling was 36%. In addition, the probability of a final folder failure in the filling of the cherry product in shift 2 and shift 3 were 62% and 58%, respectively. When analyzed on the basis of the apple product, paper failure could occur in shift 1 with a 55% probability, and final folder failure with 47% and 42% probabilities, respectively, in shifts 2 and 3. Finally, when filling the peach product, the probability of hydraulic failure in shift 1 was 47%, and the probability of photocell failure in shift 2 and shift 3 were 43% and 40%, respectively.

Table 6. Probability of Failure Mode Occurrence

	Mixed			Cherry		
	shift1	**shift2**	**shift3**	**shift1**	**shift2**	**shift3**
Final Folder	0.14	0.42	0.33	0.36	**0.62**	**0.58**
Paper	0.22	0.16	0.15	0.36	0.15	0.16
Photocell	0.09	0.14	0.13	0.26	0.22	0.25
Hydraulic	**0.56**	0.28	0.39	0.02	0.01	0.01
	Apple			**Peach**		
	shift1	**shift2**	**shift3**	**shift1**	**shift2**	**shift3**
Final Folder	0.21	0.47	0.42	0.04	0.13	0.10
Paper	**0.55**	0.30	0.31	0.23	0.18	0.16
Photocell	0.19	0.22	0.24	0.26	0.43	0.40
Hydraulic	0.05	0.02	0.03	0.47	0.25	0.34

5.4.2. Parameter Estimates and Odds Ratios for Model 2

Table 7 displays the parameter estimates and odds ratios for Model 2 based on low scrap rates (1-30 pieces). As seen in the table, compared to the paper failure mode, which had a negative effect on the scrap rate between 1 and 30, the likelihood of scraps between 1 and 30 in the reference category of hydraulic failure was approximately 7.44 (1/0.134) times more than the occurrence of scraps between 41 and 150. In addition, compared to apple juice, the probability of scrap formation between 1 and 30 in peach (the reference category) fruit juice filling was approximately 2.6 (1/0.379) times more than the formation of scraps between 41 and 150. According to another result in the table, compared to shift 2, the probability of scrap formation between 1 and 30 in shift 3, which is the reference category, was approximately 4 (1/0.245) times more than the occurrence of scraps between 41 and 150. On the other hand, in cases where the medium scrap rate (scrap pieces between 31 and 40) is in the reference category, the probability of having scraps between 1 and 30 in final folder failure was approximately 4.2 times more than in hydraulic failure. Compared to mixed fruit juice, cherry fruit juice and apple juice, the probability of having scraps between 1 and 30 in peach fruit (the reference category) juice filling was approximately 3.8 (1/0.259), 2.6 (1/0.380), and 3.8 (1/0.266) times higher, respectively, than having scraps between 31 and 40. In addition, compared to the 3rd shift, the probability of having 1 to 30 scraps in the 1st shift was approximately 2.75 times greater than having 31 to 40 scraps.

Table 7. Parameter Estimates and Odds Ratios for Model 2 (1-30)

The reference category: 41-150							
Scrap		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
1-30	Intercept	2.466	0.618	15.907	1	0.000	
	[failuremode=Paper]	-2.008	0.567	12.558	1	0.000	0.134
	[failuremode=Hydraulic]	0^b			0		
	[product=Apple]	-0.969	0.473	4.194	1	0.041	0.379
	[product=Peach]	0^b			0		
	[shift=2]	-1.405	0.449	9.781	1	0.002	0.245
	[shift=3]	0^b			0		
The reference category: 31-40							
Scrap		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
1-30	Intercept	0.469	0.422	1.234	1	0.267	
	[failuremode=Final folder]	1.442	0.465	9.630	1	0.002	4.228

	[failuremode=Hydraulic]	0b			0		
	[product=Mixed]	-1.350	0.415	10.577	1	0.001	0.259
	[product=Cherry]	-0.968	0.474	4.176	1	0.041	0.380
	[product=Apple]	-1.325	0.462	8.239	1	0.004	0.266
	[product=Peach]	0b			0		
	[shift=1]	1.009	0.380	7.063	1	0.008	2.743
	[shift=3]	0b			0		

Table 8 demonstrates that, compared to the final folder failure, the probability of scrap between 31 and 40 in hydraulic failure, which is the reference category of the failure mode independent variable, was about 4.2 (1/0.237) times greater than the occurrence of scrap between 1 and 30. Moreover, the table shows that, compared to peach fruit juice, the probability of 31 to 40 scraps in mixed fruit juice, cherry fruit juice, and apple juice filling was approximately 3.9, 2.6, and 3.8 times higher than 1 to 30 scraps, respectively. In addition, in shift 3, compared to shift 1, the probability of scrap between 31 and 40 was approximately 3.7 (1/0.365) times higher than 1 to 30 scraps. When the reference category is the scrap between 41 and 150, all of the statistically significant categories of both product and shift independent variables had a negative effect on 31 to 40 scrap formation. In this case, compared to the final folder and paper failures, the probability of scrap between 31 and 40 in hydraulic failure was approximately 4.5 (1/0.223) and 4.5 (1/0.224) times more than the probability of scrap between 41 and 150, respectively. In addition, compared to shift 1 and shift 2, the probability of scrap between 31 and 40 in shift 3 was approximately 4.6 (1/0.217) and 3.4 (1/0.294) times greater than the probability of scrap between 41 and 50, respectively.

Table 8. Parameter Estimates and Odds Ratios for Model 2 (31-40)

The reference category:1-30							
Scrap		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
31-40	Intercept	-0.469	0.422	1.234	1	0.267	
	[failuremode=Final folder]	-1.442	0.465	9.630	1	0.002	0.237
	[failuremode=Hydraulic]	0b			0		
	[product=Mixed]	1.350	0.415	10.577	1	0.001	3.856
	[product=Cherry]	0.968	0.474	4.176	1	0.041	2.633
	[product=Apple]	1.325	0.462	8.239	1	0.004	3.764
	[product=Peach]	0b			0		
	[shift=1]	-1.009	0.380	7.063	1	0.008	0.365
	[shift=3]	0b			0		
The reference category:41-150							
Scrap		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
31-40	Intercept	1.997	0.634	9.913	1	0.002	
	[failuremode=Final folder]	-1.502	0.604	6.188	1	0.013	0.223
	[failuremode=Paper]	-1.498	0.551	7.384	1	0.007	0.224
	[failuremode=Hydraulic]	0b			0		
	[shift=1]	-1.529	0.474	10.390	1	0.001	0.217
	[shift=2]	-1.224	0.438	7.816	1	0.005	0.294
	[shift=3]	0b			0		

Table 9 presents parameter estimates and odds ratios for Model 2 based on 41 to 150 scraps. Compared to hydraulic failure, the probability of scrap between 41 and 150 in a paper failure was approximately 7.4 times higher than scrap between 1 and 30. Compared to peach juice, the probability of 41 to 150 scraps in apple juice filling was approximately 2.64 times more than 1 to 30 scraps. Moreover, in shift 2, compared to shift 3, the probability of scrap between 41 and 150 was approximately 4 times higher than 1 to 30 scraps. If the scrap reference category is taken as 31 to 40, compared to hydraulic failure mode, the probability of scrap between 41 and 150 is approximately 4.5 and 4.8 times greater scrap between 31 to 40 in final folder and paper failure modes, respectively. In addition, compared to the 3rd shift, the probability of having 41 to 150 scraps in the 1st and 2nd shifts was approximately 4.6 and 3.4 times more than having 31 to 40 scraps.

Table 9. Parameter Estimates and Odds Ratios for Model 2 (41-150)

The reference category:1-30							
Scrap		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
41-150	Intercept	-2.466	0.618	15.907	1	0.000	
	[failuremode=Paper]	2.008	0.567	12.558	1	0.000	7.449
	[failuremode=Hydraulic]	0^b			0		
	[product=Apple]	0.969	0.473	4.194	1	0.041	2.636
	[product=Peach]	0^b			0		
	[shift=2]	1.405	0.449	9.781	1	0.002	4.076
	[shift=3]	0^b			0		
The reference category:31-40							
Scrap		**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
41-150	Intercept	-1.997	0.634	9.913	1	0.002	
	[failuremode=Final folder]	1.502	0.604	6.188	1	0.013	4.490
	[failuremode=Paper]	1.498	0.551	7.384	1	0.007	4.471
	[failuremode=Hydraulic]	0^b			0		
	[shift=1]	1.529	0.474	10.390	1	0.001	4.612
	[shift=2]	1.224	0.438	7.816	1	0.005	3.402
	[shift=3]	0^b			0		

The 2 MLRs for Model 2 with the reference set at a scrap rate of 41 to 150 are shown below:

$$Y_{1-30} = 2{,}466 - 0{,}060X_{final\ folder} - 2{,}008X_{paper} - 0{,}773X_{photocell} - 0{,}654X_{mix} - 0{,}527X_{cherry} - 0{,}969X_{apple} - 0{,}520X_{shift1} - 1{,}405X_{shift2}$$

$$Y_{31-40} = 1{,}997 - 1{,}502X_{final\ folder} - 1{,}498X_{paper} - 0{,}970X_{photocell} + 0{,}696X_{mix} + 0{,}441X_{cherry} + 0{,}356X_{apple} - 1{,}529X_{shift1} - 1{,}224X_{shift2}$$

With these MLR models, Equation 1 calculates the probabilities of the scrap rates that could occur are calculated as to which product is filled in which shift and which failure occurs. The results of these models are presented in Table 10. The cells with the highest probability are highlighted, and those with a probability of over 50% are marked in bold.

6. Conclusion

In this study, failure analysis of a juice filling machine was conducted and two MLR models were established for this purpose. In the first model, where failure mode, which has a significant effect on the performance of a machine, is the dependent variable, the effect of product and shift parameters on failure modes in the machine was investigated. In the second model, the relationship of product, shift, and failure mode independent variables with scrap rates was analyzed. At the end of the study, all analysis results were evaluated together.

The statistical results of the study demonstrate that while filling the mixed product, hydraulic failure should be expected in shift 1 and shift 2. In case of this failure, a low (between 1 and 30) level of scrap may occur. In addition, it is possible for final folder failure to occur while this product is being filled in shift 2. In this case, there is a high probability of low-level scrap. As a result, low scrap can be expected in the filling of the mixed product. The failure mode that draws attention in the cherry product is final folder failure. It is highly likely that final folder failure will occur in all three shifts while this product is being filled and that low levels of scrap can be expected across all three shifts. It is highly likely that paper failure can occur in shift 1 when the apple product is being filled. In this case, a low level of scrap is formed. On the other hand, when this product is being filled in shift 2 and shift 3, final folder failure can be expected. In both cases, a low level of scrap occurs. In the filling of the peach product, the occurrence of hydraulic failure in shift 1 is higher than other failures. A low scrap rate is likely to occur when this failure occurs. In addition, the occurrence of photocell failures in the filling of this product in shift 2 and shift 3 is higher than other failures. In this case, a low level of scrap is likely to occur in both shifts. All these interpretations were made according to the highest probability values. The likelihood of other failure modes and, if these failure modes occur, the likelihood of scrap levels can be examined from these tables. For example, in shift 2, the probability of paper failure in the filling of the mixed product is low, but when it occurs, a high level of scrap (between 41 and 150) can be expected. According to these results, the content and box structure of mixed, cherry, and apple products should be examined and the effects on the final folder unit of the filling machine should be investigated. Moreover, unlike other products, paper failure occurs in the filling of the apple product. This difference may require monitoring of the automatic splicing unit when this product is being filled. Furthermore, the prominent failure in the filling of the peach product is photocell failure. Investigation should be made into way the barcodes on the box are not ready by the photocells by examining the design of the product box. Finally, these models can provide a more effective analysis by incorporating humidity, temperature, and pressure data that can be obtained using sensors placed in the units that make up the filling machine.

Table 10. Probability of scrap rates

	Mixed											
	shift1				**shift2**				**shift3**			
Scrap	**Final folder**	**Paper**	**Photocell**	**Hydraulic**	**Final folder**	**Paper**	**Photocell**	**Hydraulic**	**Final folder**	**Paper**	**Photocell**	**Hydraulic**
1-30	**0.67**	0.22	0.43	0.46	0.42	0.09	0.21	0.22	**0.57**	0.16	0.30	0.28
31-40	0.14	0.32	0.31	0.41	0.29	0.45	0.49	**0.63**	0.33	**0.64**	**0.59**	**0.67**
41-150	0.19	0.45	0.26	0.13	0.30	0.46	0.30	0.15	0.10	0.20	0.11	0.05
	Cherry											
	shift1				**shift2**				**shift3**			
Scrap	**Final folder**	**Paper**	**Photocell**	**Hydraulic**	**Final folder**	**Paper**	**Photocell**	**Hydraulic**	**Final folder**	**Paper**	**Photocell**	**Hydraulic**
1-30	**0.71**	0.26	**0.50**	**0.54**	0.48	0.12	0.26	xx	**0.65**	0.21	0.38	xx
31-40	0.10	0.26	0.24	0.33	0.22	0.38	0.42	xx	0.25	**0.57**	**0.51**	xx
41-150	0.18	0.47	0.26	0.13	0.30	**0.50**	0.33	xx	0.10	0.22	0.12	xx
	Apple											
	shift1				**shift2**				**shift3**			
Scrap	**Final folder**	**Paper**	**Photocell**	**Hydraulic**	**Final folder**	**Paper**	**Photocell**	**Hydraulic**	**Final folder**	**Paper**	**Photocell**	**Hydraulic**
1-30	**0.62**	0.19	0.40	xx	0.38	0.08	0.19	0.21	**0.56**	0.15	0.29	0.28
31-40	0.13	0.27	0.28	xx	0.25	0.38	0.44	**0.60**	0.31	**0.60**	**0.57**	**0.66**
41-150	0.25	**0.54**	0.32	xx	0.37	0.54	0.37	0.19	0.13	0.25	0.14	0.06
	Peach											
	shift1				**shift2**				**shift3**			
Scrap	**Final folder**	**Paper**	**Photocell**	**Hydraulic**	**Final folder**	**Paper**	**Photocell**	**Hydraulic**	**Final folder**	**Paper**	**Photocell**	**Hydraulic**
1-30	**0.83**	0.41	**0.67**	**0.73**	**0.38**	0.08	0.19	0.21	**0.81**	0.37	**0.59**	**0.58**
31-40	0.04	0.16	0.13	0.17	0.25	0.38	0.44	**0.60**	0.12	**0.39**	0.30	0.37
41-150	0.13	0.44	0.21	0.10	0.37	**0.54**	0.37	0.19	0.07	0.24	0.11	0.05

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