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STATISTICAL MULTIVARIATE ANALYSIS OF THE DOSING PROCESS RESULTS FOR PREDICTIVE PRODUCTION AND QUALITY MANAGEMENT – A CASE STUDY FROM THE FOOD INDUSTRY

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Purpose: The aim of this article is to perform a multivariate statistical analysis of package filling process results for predictive production and quality management. The article presents a case study from the food industry that demonstrates the feasibility of using an appropriate set of control charts for ongoing and predictive production and quality management.
Design/methodology/approach: The objectives of the article were achieved through the use of Statistical Process Control (SPC) tools, in particular control charts. The control charts used include both traditional numerical chart such as Xbar and S and special charts such as MA, EWMA, CUSUM and GCC.
Findings: SPC tools such as control charts have proven to be extremely useful in monitoring the filling process and predicting future performance. By carefully monitoring the process using traditional and special control charts, it is possible to quickly identify small, gradual or sudden changes that may occur in the production process before the process gets out of control.
Research limitations/implications: The research will continue by identifying additional factors that affect the quality of the product, particularly as regards precision and accuracy of dosing, and by evaluating the process studied in terms of its ability to meet customer requirements. Other statistical techniques will also be used to identify patterns and relationships between the various parameters of the process under study. This approach will provide more comprehensive information about the quality and ability of the dosing process to meet customer requirements..
Practical implications: By implementing the right SPC toolkit and using dedicated software that significantly speeds up data analysis, companies can effectively control the quality of the production process. By monitoring the behaviour of the process over time and detecting small changes and trends, it is possible to respond to potential problems in advance.
Originality/value: This article is intended for production process managers who want to learn how to use the right SPC toolkit to obtain information about the process behaviour and the moments when intervention actions should be taken.

Keywords: production and quality management, SPC, stability analysis, prediction, improvement.

Category of the paper: case study.

1. Introduction

Filling packaging is a key process in industries involving bulk, liquid or semi-liquid products (Fellows, 2009). The process involves placing the correct amount of product into a package, which is then sealed and ready for distribution (Brennan, Grandison, 2011). The quality of the filling process affects the cost of production, the efficiency, effectiveness of the production process and the quality and safety of the products (Herod, 2006). Both too much and too little product in packaging can have negative consequences for the company: technological, legal, cost, image (Mettler, Toledo, 2011). Effective management of the packaging filling process is crucial for efficient production management. Optimising this process can contribute to optimising the use of raw materials, reducing production costs, increasing productivity and reducing the duration of the production process (Kusinska, 2009; Krynke et al., 2022). The quality of the filling process is an important factor affecting the quality and safety of the final product (Fellows, 2009; Brennan, Grandison, 2011).

Organisations are constantly looking for new tools, methods and systems in order to maximise profits and strengthen their competitive advantage (Rosak-Szyrocka, 2018). Controlling, managing and improving the quality of any process, including packaging filling processes, is possible with statistical process control (SPC) tools such as control charts and quality capability indices (Montgomery, 2012; Lim et al., 2014; Knop, 2021a). Statistical analysis of a process using SPC tools makes it possible to assess its behaviour over time, identify trends and changes in the process, and understand the impact of common and special causes affecting the process (Wheeler, 2000; Webber, Wallace, 2007). In this way, process managers can react quickly to abnormal and unfavourable deviations in the process and prevent quality problems, including product nonconformities in an effective manner (Ulewicz et al., 2023). The results of using SPC tools can be the basis for process changes, staff training or machinery upgrades (Madanhire, Mbohwa, 2016). The result can be a reduction in production costs, increased efficiency and effectiveness of the production process (Soriano et al., 2017). SPC tools are a very important tool in the Six Sigma concept (Wojtaszak, White, 2015). Statistical Process Control (SPC) is a subset of Six Sigma and is used to monitor operations to identify any anomalies and suggest possible solutions.

Modern production and quality management and control requires anticipatory actions regarding the production process and quality creation processes based on the prediction of process behaviour (Wolniak, 2021). Predicting future scenarios in a process, especially unfavourable ones, enables appropriate preventive actions to be taken and keeps the process on track (Spree, 2021; Knop, Ziora, 2022). SPC tools can assess the predictability of processes in the future based on current and historical process behaviour (Wheeler, 2000). Control charts can identify unusual large changes in a process, indicate trends in the process, small but progressive changes in the process, thus enabling efficient and effective production and quality management (Oakland, 2003; Nolan, Provost, 1990). The efficient use of control charts in production and quality management avoids negative scenarios in the process and corrects problems in the process before they have more serious consequences (Lepore et al., 2016). It is important for process managers to use the right SPC tools properly and to be able to read the signals from them that tell them what is happening in the process and how the process can be improved (Deming et al., 2012).

The aim of this study is to statistically analyse multivariate data from the dosing machine for predictive quality and production management. The article is a case study, presenting an approach to the statistical analysis of results from a process using SPC tools to alert process managers to negative situations in the process. Through the use of the SPC tools presented in the article, the author believes that it is possible to alert managers to small and minor changes in the process so that they can take appropriate preventive action. As one of the principles of a flexible and adaptive management approach states, it is better to act and make decisions based on partial knowledge of the future than to rely solely on a full understanding of the past (Fred, 2010). Predicting the behaviour of a process over time can help managers prepare for different scenarios and can be part of risk analysis. The company surveyed had not previously used SPC tools. This article aims to show the benefits of analysing process data using SPC tools in the context of predictive production and quality management.

2. Methods

The research was carried out at a food production facility located in the Silesian Voivodeship in Poland. The process analysed was the filling of a product into packaging of the Twist Off (TO) 190 jar type. The device tested was a dispenser of Dutch manufacture, 1988, designed for filling glass containers with various thick masses, such as ketchup, tomato concentrate, jams, etc. (Technical and operating documentation of the dispenser, 1988). The research concerned the process of filling TO 190 jars with a product of the tomato concentrate type with an extract of 30% with the declared nominal quantity in the jar - 180g. The filling device under study performs the filling function by means of 12 suction and pressing cylinders. The process analysed is therefore a multi-stream process, where 12 jars are filled simultaneously during one machine cycle.

The temporal scope of the filling process analysis covered one year of operation of the tested device, in which the Quality Control Department of the company recorded data on the actual nominal quantity of tomato concentrate filled into TO 190 jars (net weight of the product in the package) on the product manufacturing process chart in the inter-operational test protocol.

In order to comply with the requirements of the Pre-packaged Goods Act of 7 May 2009 regarding the permissible negative value of the error of the quantity (shortage) of the pre-packaged good and the average actual quantity of the product in the package in relation to its nominal quantity (Pre-packaged Goods Act of 7 May 2009), the tested filling machine was set to a dose size value of 183g (i.e. with an allowance in relation to the nominal value of 180g), taking into account the potential variability of the dose size in the individual filling pistons of the machine. While the Act does not specify a positive value for the error in the quantity of the packaged good (over-packaging), dosage sizes above 189g are considered by the company to be problematic in terms of the ability to properly close the jar in the next process step (which is due to the inability to create the correct vacuum to properly close the jar) and expose it to financial loss (every excess gram over the nominal value costs the company money). Too little product in the package, not conforming to the declared weight, and on the other hand, filling too much product - causes losses, and have legal and image consequences for the company.

The statistical analysis of the filling process data carried out was to show whether the dosing process carried out by the filling machine under investigation behaved in a stable and predictable manner over the time period analysed. The analysis was to indicate at which specific time points there were signals of unfavourable changes in the process.

SPC tools from the numerical evaluation control chart group will be used, both classic and special tools to analyse the filling process in terms of changes in stability and to assess the predictability of the results. The analysis will include results from the unit under study and from its individual streams, i.e. the 12 filling pistons. The main objective of the dosing process managers is to keep the net product weight in the jars constant at 183g, regardless of the filling piston used, with a possible minimum variation in results. If there are multiple extremes in a particular piston compared to the others, there is likely to be a problem with that particular filling piston.

As part of the initial statistical analysis of the filling process, an analysis of the distribution of the results using a histogram will be carried out and the conformity of these results to a normal distribution will be assessed (Frost, 2020). In addition, a box-and-whisker plot of the median - quartiles - range type will be made to determine the shape of the data distribution, the type of skewness and the presence of possible outliers in the data set (Frost, 2020; Knop, 2018).

Control charts will be used to assess the stability and predictability of the net mass results for the entire period analysed. The control chart is a widely used Statistical Quality Control (SQC) or Statistical Process Control (SPC) tool to find the assignable cause of variation and detect any changes in the process (Sałaciński, 2015). Generally, Shewart Control Chart for variables, such as Xbar-R and Xbar-S are most commonly used (Kiutras et al., 2007). An Xbar-S control chart will be developed and run pattern tests (also known as configuration tests) (Nelson, 1984; Kiutras et al., 2007) will be performed to detect non-random patterns of points on the control chart and to identify signs of process instability.

Dosing process managers are keen to detect the timing of adverse process changes that cause an increase or decrease in the average net weight of the product in the package in relation to the process objective. There is a need to detect these changes earlier to avoid quality problems and excessive financial losses. Special types of control charts will be used to identify and give early warning of negative trends in the filling process. In some cases the traditional Shewart control charts may not give good results, especially when the data has small average shift. Alternative control charts are needed, such as Moving Average (MA), Exponential Weight Moving Average (EWMA) (Kalgonda et al., 2011; Febrina, Fitriana, 2022; Sukparungsee et al., 2020), Cumulative Sum (CUSUM) (Koshti, 2011; Papić-Blagojević et al., 2016; Riaz et al., 2011) or others.

A MA moving average control chart will be used, with different window sizes, for noticing small changes and trends. In the construction of the MA chart, a window size of 6 will be adopted to notice minor changes in the process average, and a window size of 12 to help notice a global trend in the process. The crossing of control boundaries by points on this control chart will indicate a significant change in the process in terms of the mean performance value to which a response should be made.

The EWMA Xbar-S control chart will be used to detect small variations in the dosing process that may be difficult to spot with traditional control charts such as the mean and standard deviation control chart. This will enable managers to react quickly to potential deviations and identify special causes in the process. The EWMA chart takes historical data and weighs it exponentially using the Lambda parameter, which determines the percentage of influence of the current sample and previous samples on a point on the control chart. Typically, Lambda values between 0.2 and 0.3 are considered to give an appropriately smoothed but still sensitive control. In this case, a Lambda parameter value of 0.25 was adopted, which means that 25 per cent of the weight is left for the current sample and 75 per cent for the historical samples (Kalgonda, et al., 2011; Febrina, Fitriana, 2022; Sukparungsee et al., 2020).

A CUSUM single-value control chart will be used to accurately capture the moment in time when there was an abrupt change in the dosing process compared to the process average (Koshti, 2011; Papić-Blagojević et al, 2016; Riaz et al., 2011).

A graph of the mean ± errors type will be used, where the errors are taken as the 95% confidence interval for the mean value in order to identify the behaviour of the samples due to the mean value of the results (Jobson, 1992), which indicate an abrupt change in the dosing process.

In order to verify which filling machine pistons generated the most extreme results with signs of instability in these net mass results, the use of the XM-R multiple-stream Group Control Chart (GCC) was proposed (Boyd, 1950; Jirasettapong, Rojanarowan, 2011; Liu et al., 2008; Mortel, Runger, 1995).

A box-and-whisker graph was used, which includes information on the mean, standard deviation, minimum and maximum (Johnson, Wichern, 2007). Along with this graph, statistics such as the mean, standard deviation and coefficient of variation were also presented to show the variation in the amount of product in the pack for each filling machine plunger in relation to the average performance value and to indicate the plunger that has the best and worst performance from an accuracy and precision point of view.

A dose size stability analysis will be carried out for each piston separately using the IX-MR control chart to identify pistons with unstable results (Meneces et al., 2008).

3. Results and discussion

The result of the analysis of the statistical distribution of the net product weight over a period of 1 year of operation of the filler is presented by means of a histogram and a box-and-whisker diagram (Figure 1).

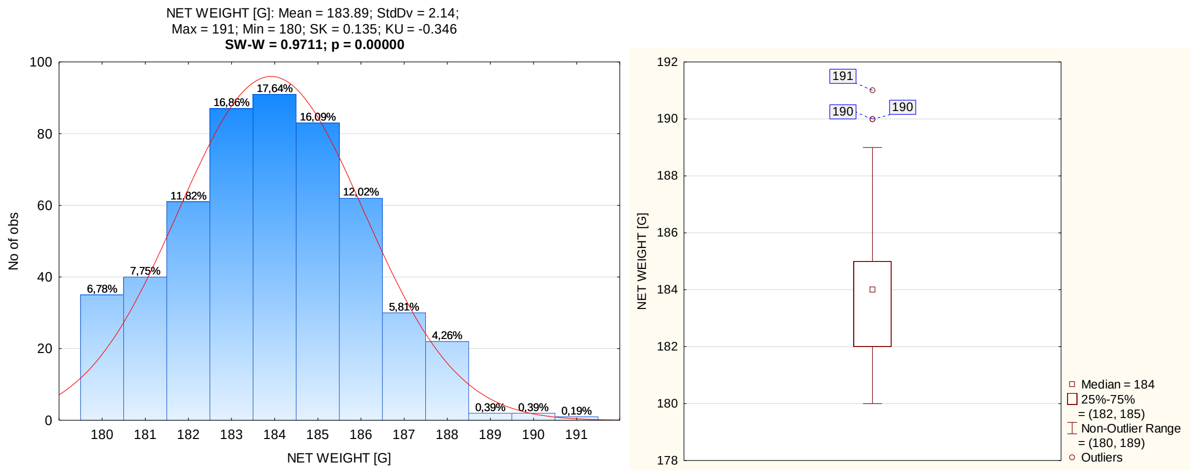


Figure 1. Distribution of the net product weight results using a histogram (a) and a box-and-whisker plot of median - quartiles - range type (b).

Source: own study with the use of Statistica 13.3 TIBCO software.

According to Figure 3a, the range of net weight results was between 180 and 190 g, with a net weight of 184 g being the most common value. The distribution of net weight is not a normal distribution, which was confirmed by tests of the normality of the distribution ($p < \alpha$). The distribution of the function is right-sided asymmetric, as evidenced by the longer right tail of the function. In the box-and-whisker plot, two net mass outliers were identified that are significantly different from the other values.

The result of the X-bar and S chart build is shown in Figure 2.

As can be seen from the X-bar and S control chart, all results on both charts are within control limits, meaning that the process is under statistical control. This indicates the stability and predictability of the process and the presence of only natural (common) variation (so-called noise) in the process. The process is stable on the R chart, which means that the distributions in the samples are consistent and there is no statistical difference between them. It is possible to predict the net weight variation for 12 samples, where the average spread will be 2.04 g, with a range from 0.72 g to 3.36 g. The process is also stable in terms of mean values, meaning that the variation between sample averages is similar and there is no statistical difference between them. It is possible to predict the average net weight for the 12 pack samples, where the long-term average would be 183.89 g, with a range from 182.08 g to 185.70 g. The configuration tests carried out on the X-bar and S charts also did not show any specific patterns of points that would indicate a deregulation of the process. As a result, the analysed process can be considered fully stable and predictable over the analysed time.

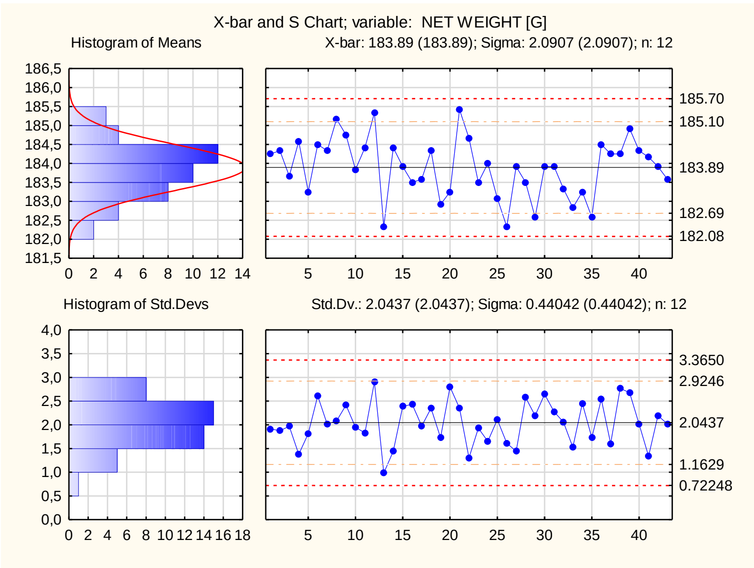


Figure 2. X-bar and S control chart for 1 year of filling machine operation.

Source: own study with the use of Statistica 13.3 TIBCO software.

The result of the MA moving average control chart design for window sizes 6 and 12 is shown in Figure 3a and b.

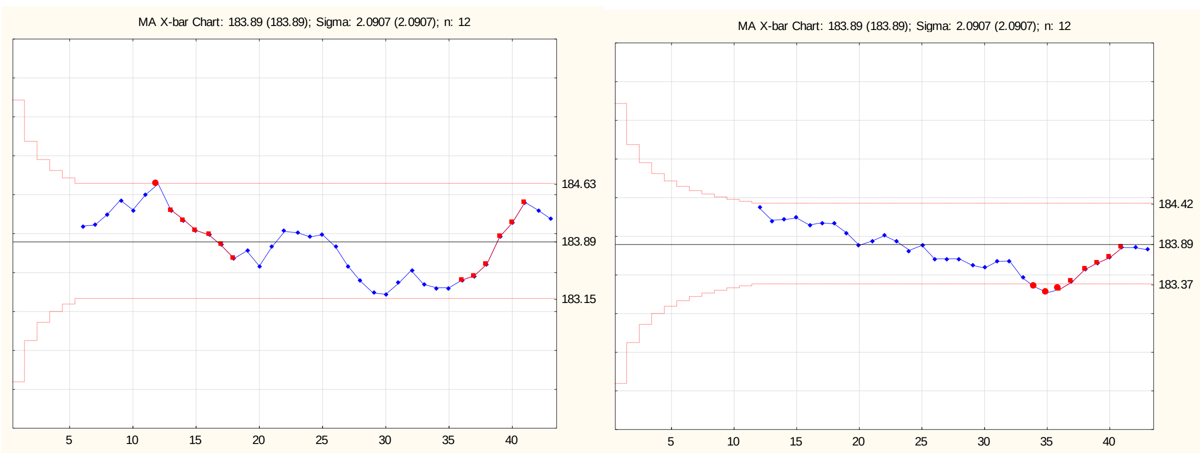


Figure 3. MA chart with a window size of 6 (a - left) and 12 (b - right).

Source: own study with the use of Statistica 13.3 TIBCO software.

When the results are averaged and smoothed on the MA control chart, using different window sizes, various changes and drifts in the moving average values and symptoms of process instability can be observed. On the MA chart with a window size of 6 (Fig. 4a), a worrying symptom of a drift of the process towards higher and higher values is observed, which persists up to sample No. 12. The process then starts to drift downwards, i.e. there is a decreasing trend in the results. A renewed upward trend is noticeable from sample No. 36 to sample No. 41. Adopting a window size of 12 and a greater smoothing of the results (Figure 4b) reveals a clear downward trend in the moving average of the results, which persists until sample No. 35. In sample Nos. 34, 35 and 36, the MA chart signals the instability of the moving average of the results by exceeding the lower control limit. From sample No. 36 onwards, there is again an increasing trend in the net mass results.

The result of using the EWMA X-bar and S chart with an assumed Lambda value of = 0.25 is shown in Figure 4.

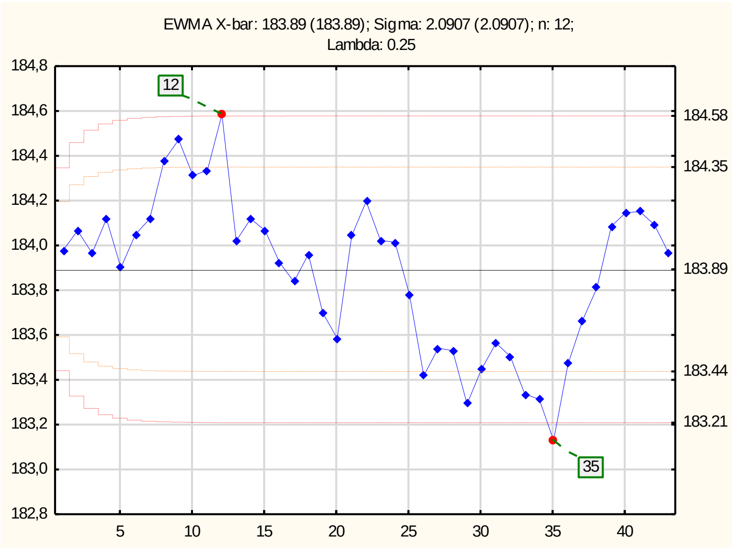


Figure 4. EWMA X-bar and S chart with Lambda = 0.25.

Source: own study with the use of Statistica 13.3 TIBCO software.

Based on the results from the EWMA chart, two significant points in time can be identified where there was a change in the trend of the filling process. The first point of trend change in the process occurred in sample No. 12, when the process started to move towards smaller and smaller values. The second point occurred in sample No. 35, when the process started to move towards larger and larger values.

The result of using the CUSUM single measurement control chart is shown in Figure 5.

As can be seen from Fig. 6, there were three moments in the filling process when there was a significant deviation from the process mean value (183.89 g). This means that there were rapid changes in the size of the dosage, which affected the overdrive of the process. The first moment of deviation occurred in sample no. 12, which contained 12 net mass measurements numbered 132-143. In this range of measurements, there were signals indicating a rapid process change in samples 142-143. The second moment of deviation occurred in the results from sample No. 21, which contained a further 12 measurements numbered 252-263, with signals of rapid change for samples Nos. 252-262. The third moment of deviation occurred in the results from sample No. 29, which contained measurements numbered 348-359, where sample No. 348 showed a significant signal of process change.

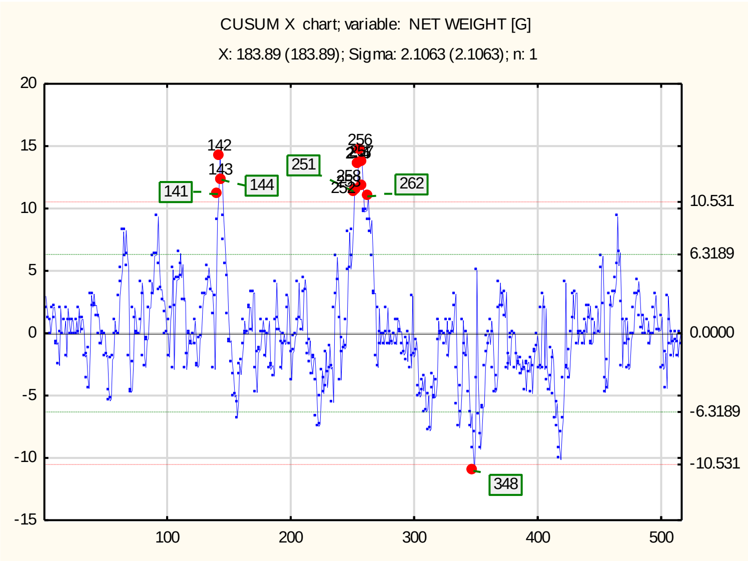


Figure 5. CUSUM chart based on individual observations of the mass of net product weight in jars.

Source: own study with the use of Statistica 13.3 TIBCO software.

A plot of mean ± errors, where the 95% confidence interval for the mean was taken as the error value, is shown in Figure 6.

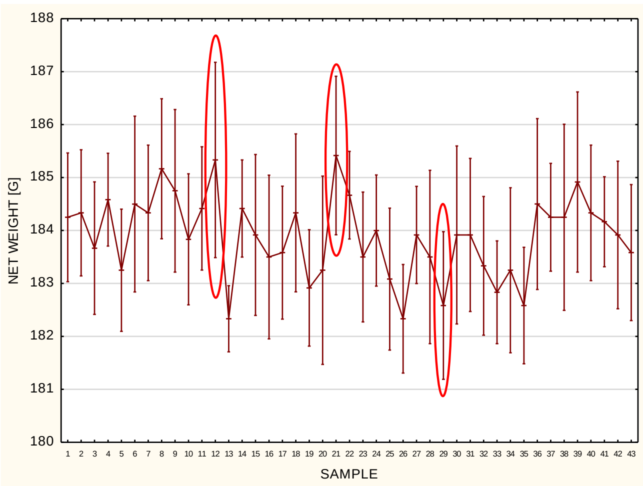


Figure 6. Mean ± errors plot (95% confidence interval).

Source: own study with the use of Statistica 13.3 TIBCO software.

As can be seen from Figure 6, in samples 12, 21 and 29, the 95% confidence interval for the mean value of these samples is either at the top of the graph (for samples 12 and 21) or at the bottom (for sample 29), indicating significant differences in mean values compared to the other samples.

The result of using the multiple stream X and MR chart type GCC is shown in Figure 7.

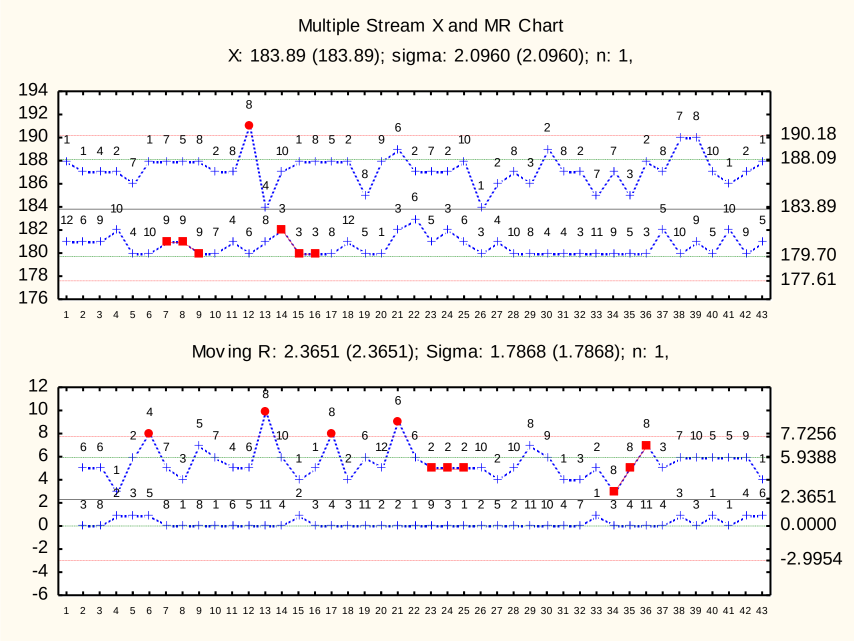


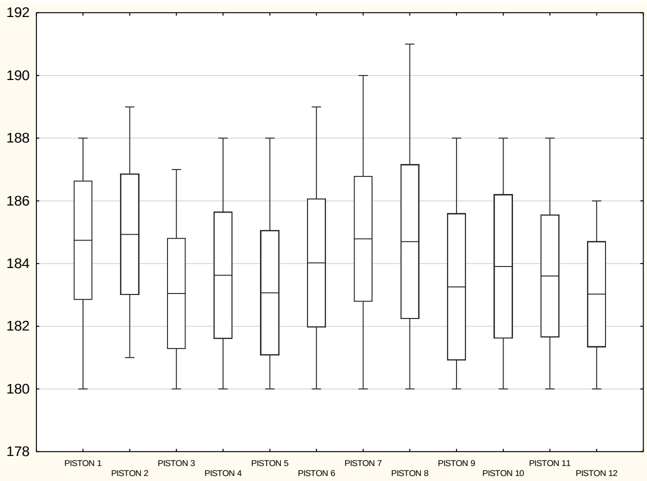
Figure 7. GCC-type Multiple Stream X and MR chart for stability analysis of results from individual filling machine pistons.

Source: own study with the use of Statistica 13.3 TIBCO software.

It can be seen from Figure 7 that the highest value of the dose size in the cross-section of all pistons was recorded for piston No. 8 in sample Nos. 12 and 39, and for piston No. 7 in sample No. 38. Among the pistons dispensing the highest amount of product into the pack in successive samples, piston No. 8 appeared most frequently (8 times), while the piston dispensing the lowest amount of product into the pack among all pistons was most frequently piston No. 9 (7 times).

A box-and-whisker plot of the mean/standard deviation/minimum-maximum type, together with statistics such as mean, standard deviation and coefficient of variation, is shown in Figure 8.

The filling machine piston that was closest to the target for this process (NOM = 183) was piston No. 12, 3 and 5. Piston No. 12 is also the piston that generated the least variation in results against the average value. It was therefore the most precise and accurate filling machine piston. The pistons of the machine that most outweighed the packages were, in turn, pistons No. 2, 7, 1 and 8. The most imprecise (off target) piston of all the machine pistons was piston No. 2, while the most inaccurate (with the greatest variability in results) was piston No. 8.



No of piston	AVG	SD	CV
PISTON 1	184.74	1.90	1.03
PISTON 2	184.93	1.93	1.04
PISTON 3	183.05	1.77	0.97
PISTON 4	183.63	2.02	1.10
PISTON 5	183.07	1.99	1.09
PISTON 6	184.02	2.05	1.12
PISTON 7	184.79	2.01	1.09
PISTON 8	184.70	2.46	1.33
PISTON 9	183.26	2.34	1.28
PISTON 10	183.91	2.30	1.25
PISTON 11	183.60	1.95	1.06
PISTON 12	183.02	1.68	0.92

Figure 8. Box-and-whisker plot of mean/standard deviation/minimum-maximum for pistons 1-12, together with statistics such as mean, standard deviation and coefficient of variation.

Source: own study with the use of Statistica 13.3 TIBCO software.

The use of the Individual and MR charts indicated that pistons numbered 4, 6 and 8 were characterised by instability in terms of variability as measured by the moving range. This instability was due to the significantly different values of the magnitude of the doze between two consecutive results (the current sample, for which the divergence occurred, and the previous sample) for these analysed pistons.

4. Summary

The article presents an analysis of the filling process, with net weight as the outcome measure. Various SPC tools such as control charts (X-bar and S, MA, EWMA, CUSUM, IX-MR multiple-stream charts GCC type, IX-MR chart) and mean ± error plots were used to monitor and identify changes in the filling process.

The results of using the traditional control chart showed that the filling process was under statistical control throughout the entire study period. Using special control charts, signals of process deregulation were indicated. Two significant points in time were identified where there was a change in the process trend. Sudden changes in the size of the dosage were observed, which resulted in an overdrive of the filling process. In addition, there were other points at which the process showed a change in trend. Observation of the results on special control charts provided additional information about the filling process, minor trends and changes in the process that could not be observed with traditional control charts:

- in sample No. 12 from result No. 141, in sample No. 21, from result No. 251, in sample No. 29 for result No. 348 and in sample No. 35, the process should be considered to have gone out of control,

- the highest value of the dose size in the cross-section of all pistons was recorded for piston No. 8 in sample Nos. 12 and 39, and for piston No. 7 in sample No. 38,
- the filling machine pistons that performed closest to the target in the filling process were pistons No. 12, 3, and 5. Among them, piston No. 12 exhibited the least variation from the average value, making it the most precise and accurate,
- pistons No. 2, 7, 1, and 8 were the pistons that caused the greatest deviation in package weights. Among them, piston No. 2 was the least precise (off target), while piston No. 8 showed the highest level of inaccuracy (greatest variability in results).

The overall conclusions of the conducted analyses are as follows:

1. SPC tools such as control charts have proved useful in monitoring the filling process and predicting the future. Careful monitoring of the process using a variety of control charts, both traditional and special, allows for the rapid identification of minor, progressive and sudden changes in the process and makes it possible to respond to these deviations.
2. The use of SPC tools makes it possible to anticipate future changes in the filling process, which allows for a rapid response and correction of the process.
3. The statistical analyses carried out in the area of the process under study provide important information for the food company. They allow for better production control and quality management by identifying unfavourable changes and trends in this process, which provides an opportunity to take appropriate improvement actions.

The conclusions of this article highlight the benefits that the application of SPC tools can bring to the food industry, enabling better production control and quality management of food products.

The conclusion of the analysis is that improvement actions must be taken to improve the precision and accuracy of the dosing process. It is recommended to analyse the technical condition of the parts responsible for the dosage precision in the filling machine and possibly replace these parts with new ones, as well as to continuously monitor the machine percentage of planned production by means of the OEE indicator (Knop, 2021b). In addition, maintenance of the filling machine should be systematic in order to keep it in good working order. In order to further optimise the filling process, it is recommended to continue monitoring and analysing the results and to introduce systematic process improvement using SPC tools and the Kaizen concept tools, such as e.g. 3G analysis, Quick Kaizen (Gajdzik, 2023) and to implement computer system supporting the management of machines operation and maintenance in the analysed company for, among other things, efficient optimisation of maintenance-repair works of the filling machine (White, Freis, 2019).

There is great potential for further research in the area of filling process analysis in the food industry. Research into the optimisation of the filling process will be continued by identifying other factors influencing product quality in terms of dispensing precision and accuracy, and using other statistical techniques and combined quality management tools (Czerwińska, Piwowarczyk, 2022) to identify patterns and relationships between different process parameters, which can provide more comprehensive information on the quality and ability of the dispensing process to meet customer requirements. This type of research has the potential to bring significant benefits in terms of improving the quality, efficiency and effectiveness of production processes.

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