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CAPABILITY ANALYSIS OF DRIFT-INHERENT PROCESSES: CASE OF NAIL WIRE DRAWING

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ABSTRACT

Purpose: The central purpose of the study is to model the process capability of drift-inherent manufacturing processes by testing the efficacy of a novel approach that filters trend from raw process data before applying statistical process control tools. A secondary aim was to ascertain the intrinsic capability of the process following the filtering.

Design/Methodology/Approach: Specifically, the study focused on processes in a nail-wire drawing and tested a method for analysing data from naturally-drifting processes that involves filtering trends from data before applying appropriate tools to verify the state of statistical control and capability of the process. The physical foundation for this work is based on data collected from a nail-wire drawing process A total of 250 data points were gathered over 50 days in two successive instances of 125 points, each spanning 25 days. Data were checked for normality followed by mathematical conditioning to filter out the wear trend before analysis by normal statistical process capability and control chart procedures.

Findings: Results show that the proposed method is effective for tracking hidden effects in steadily drifting processes such as those associated with wear. After filtering, the data is found to fall within product specifications, though robust statistical control was still required through appropriate measures.

Research Limitation: To investigate the intrinsic nature of the process outside of the process, material wear is assumed to be the sole source of the inherent drift. In processes where several sources of inherent drift are present, this may pose a problem. Additionally, the study focused on just one plant; however, data from other similar plants will be needed to buttress the findings and widen the scope of applicability of the findings.

Practical implication: The competitive pressures of today's marketplace are increasingly forcing companies to place premium emphasis on product quality while aiming at the lowest costs possible. The study recommends continuous and sustained efforts to reduce variation in manufacturing processes to brighten firms' competitive survival.

Social implication: The study will bring new knowledge to metal product manufacturers that can help them deliver high-quality products and value for money to consumers.

Originality / Value: New insights afforded by the study's approach include revelations of otherwise hidden measurement errors as well as undersized finishing-die. Any other out-of-control occurrences can then be more easily tracked and identified and root-cause analysis applied to eliminate them. This is a practical study that seeks to develop an innovative way to monitor the quality of processes whose tracking is made difficult by inherent drift. The easy-to-adopt methodology can be implemented by metal product manufacturers grappling with drift-inherent processes.

Keywords: *Continuously drifting. filtering approach. metal. process capability.*

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INTRODUCTION

Process drift occurs in many manufacturing processes whereby process parameters deteriorate, adversely affecting quality. This study tests a method for analysing data from a naturally-drifting process that involves filtering trends from data before applying appropriate tools to verify the state of statistical control and capability of the process. The secondary purpose is to investigate the intrinsic nature of the process outside of tool wear, which in this study is assumed to be the sole source of the inherent drift. Any other out-of-control occurrences can then be more easily tracked and identified and root-cause analysis applied to eliminate them. The physical foundation for this work is provided by data collected from a nail-wire drawing process.

Nail Production

Nails are a very crucial component in the building and furniture industries. They are predominantly wood fastening devices specified in terms of diameter and length as well as material. These specifications often determine the kinds and sizes of wood they can be used to fasten. Nails of small diameter are used for fastening woods that are softer in nature or thinner. The nail production process comprises two main stages: drawing the input material to the desired diameter, and then cutting it to appropriate lengths. Table 1 displays some standard nail diameters and their corresponding lengths.

Table 1: Standard diameter ranges and corresponding length specifications of nails

Diameter Range (mm)	**Nail Length**	
	(in)	**(mm)**
6.0 – 6.4	6	152.4
4.6 – 5.4	5	127
3.6 – 4.5	4	101.6
2.5 – 3.0	2.5	63.5
2.0 – 2.4	2	50.8
1.6 – 2.0	1.5	38.1
1.0 – 1.4	1	25.4

Source: Donyma Steel Complex (2021)

Process Variation, Capability, and their Measurement

Variation in manufacturing processes is undesirable, but scope always exists for reducing it a little more to improve product quality a little further. Statistical process control (SPC) is a tool that tracks process variability to detect the point where the process may begin to drift out of statistical control (Koppel & Chang, 2016; Aravind, Shunmugesh & Akhil, 2017). Process capability analysis (PCA) is an engineering decision-making tool in SPC applied within the normality of the process to assess its capability to meet defined specifications (Singh et al., 2018). It can be used to quantify variability in areas such as vendor selection, specification of process requirements for new equipment, prediction of a process's potential to hold tolerances, aid for assisting product designers in selecting or modifying a process, and in formulating quality improvement programmes (Saha & Majumder, 2016; Aravind et al., 2017). Process capability analysis, in turn, finds practical, quantitative expression in process capability indices (PCIs), used in representing the actual level of capability (White, 2021; Liu & Li, 2021). They are useful for analysing the capability and predicting the performance of a process by providing a numerical measure of the ability of the process to meet the requirements of customers

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expressed in terms of product specification limits (Rao, Albassam & Aslam, 2019; de-Felipe & Benedito, 2017; Selmi, 2018; Tomohiroa, 2020).

Machine capabilities in the short term need to be known, and any indications of excessive variations eliminated so that the overall process can be maintained and even improved. As well, the environment of manufacturing will affect the capability of the process in the long term. For this reason, a short-term sampling plan cannot be used to predict the status of the process (its capability) in the long term (Chalisgaonkar & Kumar, 2014).

Inherently Drifting Processes

In normal process analysis, once the natural variation in the process has been ascertained and its statistical normality established, determining its natural capability is usually a straightforward matter. A problem arises, however, if this procedure is applied directly to processes inherently characterised by steady drift such as tool wear in metal drawing operations. This drift makes a direct application of statistical process control charting for product quality tricky and could introduce serious flaws depending on how it is handled. Worse, it could mask any underlying abnormal patterns in the data such as non-normality. Wire drawing, by its nature, falls in this category. If the capability of such a process is determined using standard procedures erroneous results may be obtained.

In a drifting process the possible causal factors may be linked to one or more of the following: (a) raw material properties, (b) die metallurgy, (c) die geometry, (d) drawing-die speed/feed, and (f) the human factor dimension. And if these factors are monitored and controlled, one may be able to simply put a rule in place to change the dies after a certain number of parts are produced or hours elapsed after which an appropriate action is taken (Figure 1, QI Macros, 2022). Even though this method can offer some solution to the steady-wear problem, it is not an ideal option for tackling other assignable causes unrelated to the steady drift. Once the trend line is known the nature of the wear is predictable. In this work we assume there are no steady drifts other than the one caused by progressive wear.

Some of the existing methods for handling data from continuously drifting processes are based on the application of offsets after the process has drifted to a pre-defined limit. An example of such a process is depicted in Figure 1. An obvious deficiency of this method is that it may fail to reveal all possible hidden effects.

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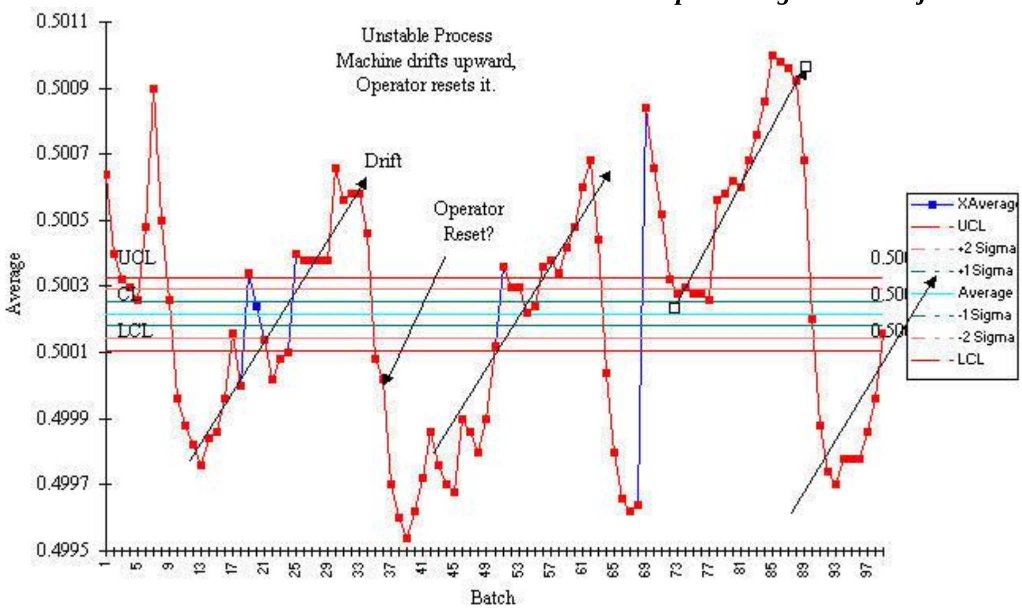

Figure 1. Unstable process showing machine drift (QI Macros, 2022)

Other methods employ slanting control limits parallel to the inclined average line. However, beyond tracking drift these sloping limits are of little value in addressing any other out-of-normal deviations that may be present in the process. Some recent works have focused on using direct succession and weak-order behavioural relationships to identify change points (Ostovar, Leemans & Rosa, 2018).

Singh et al (2017), on their part, undertook a techno-economic and process capability analysis on investment-cast components using five different process routes to obtain values of process capability indices. Duro (2017) analysed process drift and shift simultaneously by computing the difference between each data point and the mean of the sample while computing the variance. He preserved the order of data to distinguish between shift and drift. Kumar, Ranjan, and Singh, (2022) employed Taguchi orthogonal array to analyse dimensional accuracy as a process capability. Zheng, Wen and Wang (2017) developed a model for detecting process drifts using event logs; Pawar, Bagga, and Dubey (2021) investigated links between process capability and manufacturing rates, while Maaradji, Dumas, Rosa and Ostovar (2016) developed an automated online statistical model for detection of process drift. Their tests and observations led to a model for trade-offs between classification accuracy and drift detection delay. Yeshchenko, Ciccio, Mendling, and Polyvyanyy (2022) explored the challenges of drift categorization and quantification in the concept of process mining. They proposed a novel technique (Visual Drift Detection) for managing process drifts which works by clustering declarative process constraints and applying change point detection on the identified clusters to detect drifts.

In addition to the above methods, analytical approaches exist for handling data from continuously drifting processes. Refer, for example, to a method discussed in Doty (2009) in which periodic averages are plotted on the chart with sloping centreline and control limits. Any assignable causes are indicated by points plotting outside the slanting upper and lower control limits, respectively represented by:

$$y = (a + 3\sigma/\sqrt{n}) + bx$$
$$y = (a - 3\sigma/\sqrt{n}) + bx$$

where the constants *a* and *b* are determined from:

$$a = \frac{\sum_{i=1}^{n} y_i - b\sum_{i=1}^{n} x_i}{n} \qquad (i)$$

$$b = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i * \sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \qquad (ii)$$

The analyst looks to reduce the overall process variability, but the control will come from tracking variation at each setting. As the adjustment (driven by tool wear) is made, it needs to be established whether it is just the global mean shifting or it is the within-group standard deviation deteriorating as well. In many instances, it is both.

Filtering the inherent trend would leave the remaining data subject only to random variations if indeed no further assignable causes are present; so that normal process capability tools can be used to evaluate the state of the process. This study presents and validates a method for handling such data that increases the likelihood of discovering possible assignable causes masked by the steady drift. Aside from rendering the use of Equations (*i*) and (*ii*) unnecessary its other merits include:

1. The equation of the trend line can be easily obtained through simple regression using application software; the gradient element can then be filtered out to obtain horizontal control lines before plotting the adjusted data points.
2. Identification and interpretation of patterns in the chart are made much easier since the control limits are now horizontal.

RESEARCH METHODS

The quality characteristic of interest in the study is drawn-nail diameter with desired specification limits between 3.6–4.5 mm inclusive. The length of the nail is 4-inch (101.6 mm). In the study, two sets of diameter readings were taken from the production process, each over 25 days and containing 125 data points from hourly readings taken five times a day through measuring callipers. Montgomery (2012) recommends a minimum of 100 observations in normal conditions for process capability study via histograms with sampling being done only when there is an indication that the process is in a reasonable degree of statistical control.

Data collection was followed by verification of statistical normality using histograms and normal probability plots. This was to ensure that using standard analytical techniques would not invalidate inferences based on the data. Next, the data was conditioned to filter out tool wear as explained in section 1. Doing otherwise would mean the centreline of the control chart for averages could not be projected as horizontal but rather sloping or even curved if the wear is not steady. Steady wear, though, is assumed in this study.

Two methods were considered for filtering the wear trend from the data (Browne, 1998). The first involves applying the principles of three-dimensional graphics to rotate the control and

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trend (data) lines about their respective intercepts so that they are horizontal. This in turn would rotate the plotted data points by the same angular measure. The required transformation is presented in Equation (1):

$$\{x' \quad y' \quad z' \quad 1\} = \{x \quad y \quad z \quad 1\}\ T(\alpha)R(\alpha) \qquad (1)$$

where $R(\alpha)$, the rotation matrix, is given as

$$R(\alpha) = \begin{bmatrix} \cos\alpha & \sin\alpha & 1 \\ -\sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad (2)$$

and the *origin* translation matrix found using:

$$T(\alpha) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -y & 1 \end{bmatrix} \qquad (3)$$

Even though the equation of the trend line is known, the angle of rotation, α, required by this method could not be determined in a straightforward manner so the method was abandoned.

The second approach, which is the one adopted in this work, involves subtracting the gradient portion of the trend line from each data point and then making up for the slight vertical shift caused by offsetting the horizontal axis at sample number 1 and not *zero.* Data conditioning and analysis were done using Microsoft Excel with Sigma XL functionality.

RESULTS AND DISCUSSION

The combined data

Figure 2 displays a scatter plot of the combined data with the sequence preserved. As expected, there is an overall, upward trend in drawn-wire diameter over time due to the continuous wearing of the drawing dies. The slightly wider variation in the second data set is likely the result of a faster rate of deterioration of the tools.

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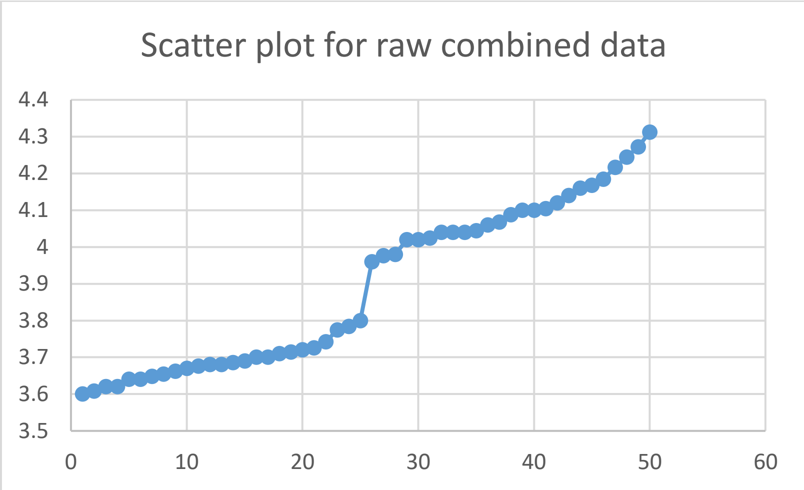

Figure 2: Scatter chart for the raw combined data

The slightly higher-than-normal wear rate observed in the last five samples of each stream could have been caused by operators speeding up the process near the end of the work day. This could be corrected by tighter supervision if proven true by investigation.

The very sharp jump in wear between the last observed data point in stream 1 and the first sample in stream 2 is likely due to a shift in a process set during the transition from month 1 to month 2. Such change in setting could be caused, for example, by a higher drawing speed or a different material stock, the former being the more likely; or perhaps by the accumulation of metallurgical effects in the die material during the second month.

Two tests of normality were performed on the combined data, yielding the normal probability plot of Fig. 3 and an Anderson-Darling (AD) *P*-Value of 0.00, which represents a failure value in the test ($p < 0.05$). Reviewing the plot, it is clear that the data imposes a curvature on the normal probability line, with some data even falling outside the 95% confidence interval. The combined data is therefore inherently non-normal. Trending in each data set is also clearly evident.

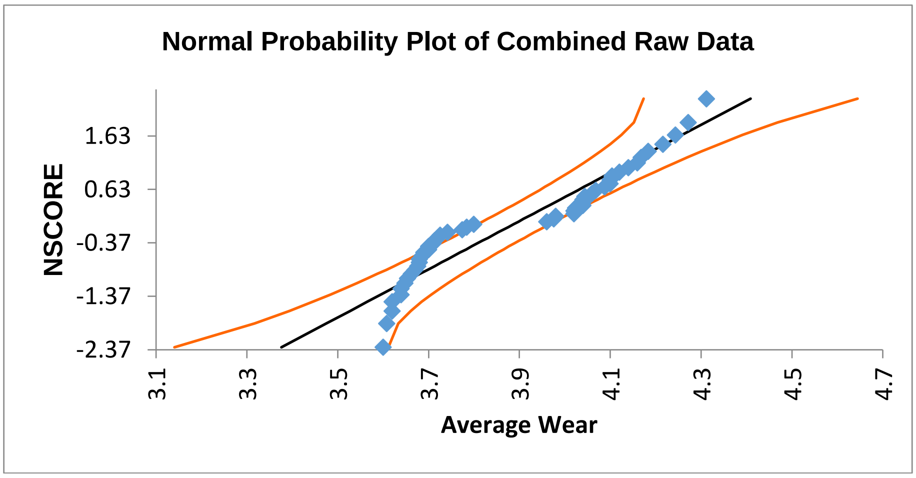

Figure 3: Normal Probability Plot for raw combined data

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No attempt was made to transform the data before finding the root causes for the outliers. The normal probability plot helps to distinguish the reasons for non-normality. Even with the outliers removed, the AD *P*-Value returned was 0.0215. A second normal probability plot produced a similar form to the first, with a significant amount of data still not lying on a straight line but instead on the boundaries of the 95% confidence curves. Trending was still present in the data and even though filtering raised the AD *P*-Value to 0.4502 the plot still retained strong indications of non-normality.

Separating the two data streams

As a consequence of the above results, each raw data stream was treated separately in a test for normality. The results are given in Table 2, along with those for the combined data. The first data set gave a sample mean and standard deviation of 3.686 mm and 0.0525 mm respectively. For the second set, these statistics are 4.099 mm and 0.094 mm. The AD P-Values are 0.8095 and 0.2689 for data streams 1 and 2 respectively, but in both cases, the normal probability plots did not indicate normality. This was due to the outliers. Calculations such as Sigma Level, *Pp*, *Cp*, *Ppk*, and *Cpk* assume normality and will therefore be affected. The descriptive statistics report in table 2 completes the picture.

Table 2: Results of Sigma XL Analysis of raw data sets 1& 2 and the combined raw data

Descriptive Statistic	Data set 1	Data set 2	Combined data
Count	25	25	50
Mean	3.686	4.099	3.892
Sample Standard Deviation	0.052	0.094	0.222
Range	0.200	0.360	0.720
Minimum	3.600	3.960	3.600
Maximum	3.800	4.320	4.320
Anderson-Darling Normality Test: P-Value	0.8099	0.2689	0.000

Dropping the Outliers and Filtering out Wear

With outliers removed, the wear-laden equations for data streams 1 and 2, found by regression, are:

$$y_1 = 0.0061x + 3.60$$

$$y_2 = 0.0101x + 3.96$$

Since the outliers are responsible for driving the non-normality in the part-to-part variation, we assume assignable causes can be found to justify their elimination. Consequently, we discard the last three data points from each stream; and after both wear and the outlying elements were removed a new normality test yielded the data in table 3, which, in conjunction with the normal probability plots of Figures 4 and 5, now confirm both data streams, especially stream 1, as normally distributed.

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Table 3: Results of Sigma XL Analysis of filtered and cleaned data set 2

Descriptive Statistic	Data set 1	Data set 2
Count	22	22
Mean	3.609	3.971
Sample Standard Deviation	0.00493	0.0132
Minimum	3.600	3.960
Maximum	3.800	4.320
Anderson-Darling Normality Test: P-Value	0.2847	0.0841

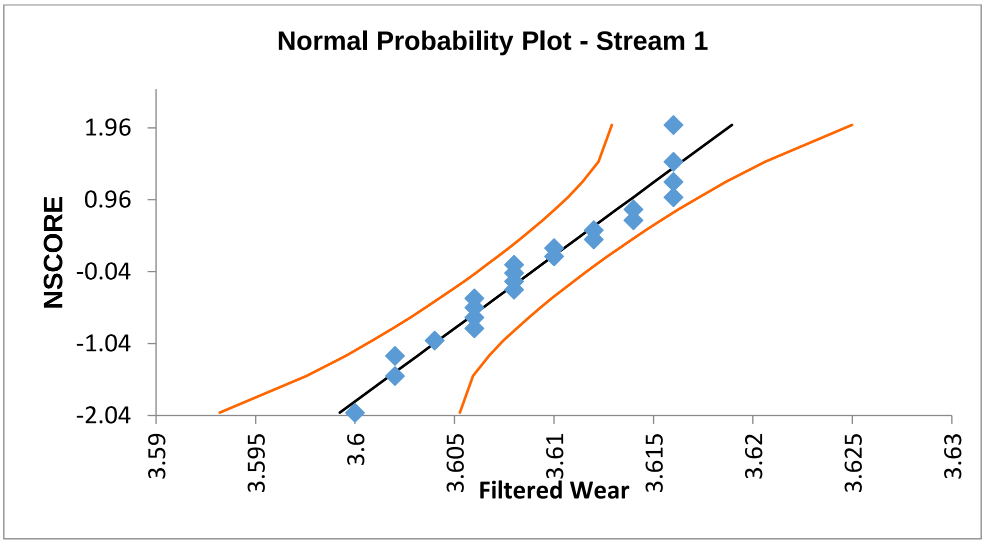

Figure 4: Normal probability plot for data stream 1 with wear and outliers removed

In the probability plots, data points are seen to follow the normal probability straight line fairly well and fall within the 95% confidence curves. Put together, and recalling that few data are ever likely to fall in a perfectly straight line, these observations point to normality in the data.

In equation form, the two transformed data sets are represented by:

$$\text{Data set 1:}\quad y'_1 = (\text{Data point} - 0.006{*}x + 0.006) \qquad (4)$$

$$\text{Data set 2:}\quad y'_2 = (\text{Data point} - 0.0099{*}x + 0.0099) \qquad (5)$$

where y' is the wear-filtered diameter, and x the sample number.

Since the data in Figure 5 fails the AD normality test but the bulk of it forms a straight line, it may be concluded that it is the outliers are still responsible for the non-normality.

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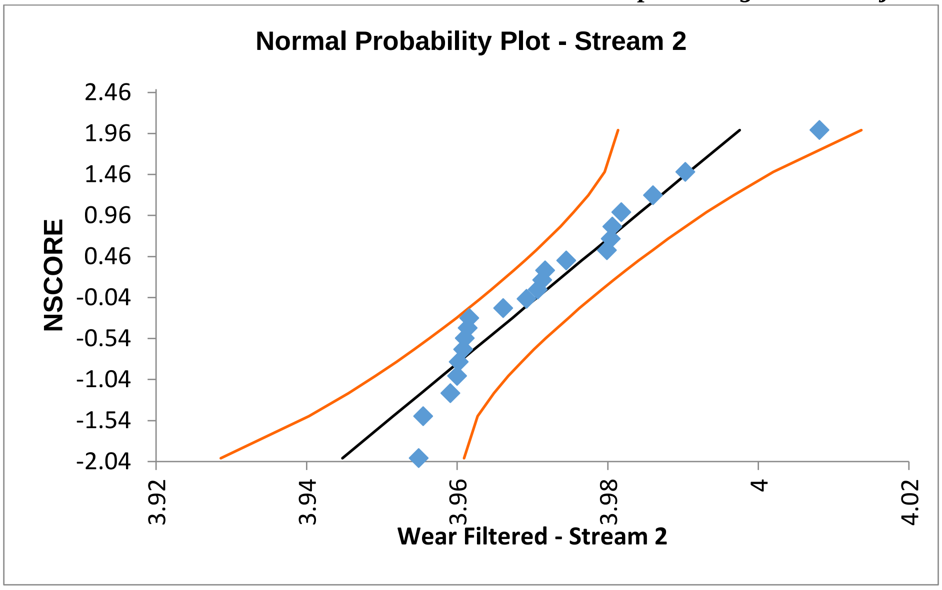

Figure 5: Normal probability plot for data stream 2 with wear and outliers removed

Control Charts

An important assumption underlying the use of control charts and capability indices is that their usual interpretation is based on normally-distributed process output. Consequently, to ascertain the true state of the process outside of the expected drift, *X*-bar charts for nail diameter (indicating both the time-to-time variability and random errors of the process) were generated from each set of transformed data (Figures 6 and 7) as well as from the combined data (Figure 8), for comparison. In addition to the +/-3 sigma limits both control charts also display +/-1 sigma and +/-2 sigma lines to aid in viewing any patterns and special occurrences. The upper specification limit (USL) for the process is 4.5 mm (Table 1).

From Figures 6, 7, and 8 it can be seen that pre-filtering the drift-laden data is effective since the control limits are horizontal and parallel, increasing the transparency and clarity of the plots and their ease of interpretation. Doty’s analytical method for handling drifting processes (2009) would have yielded slanting control limits. Further, the proposed method generates quicker responses and results than Zheng's et al., (2017) model for handling process drifts since no time is wasted in detecting, registering and processing event logs. We now turn to a detailed discussion of each data set.

Data set 1

From Figure 6 it is clear that there are no points that exceed the +/- 3 sigma limits on this chart, but we see some indication of slight instability in that some of the plotted points (from numbers 6 to 10) exhibit non-random patterns of behaviour as described by Montgomery (2012). We also observe that following the sixth data point, 5 points in a row increase in magnitude or stay constant, i.e. a general run-up. Once again, no action is triggered since the run is less than 8 points (Montgomery, 2012).

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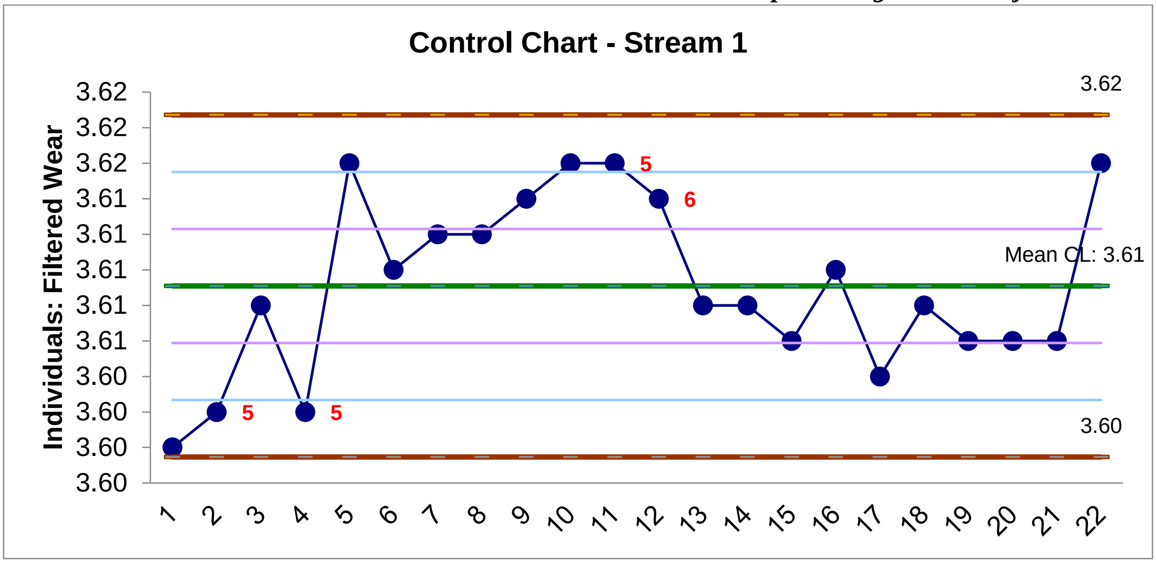

Figure 6: X-bar control chart for drawn wire diameter (data set 1, wear filtered out)

A run-down of similar length beginning with the 11th point is also observed, but the former run occurs on the same side of the centreline. We further note that 10 of the 22 points plot above the centre line, while 12 plot below it, which is a fairly even distribution. Some authoritative sources, including Montgomery (2012) postulate that a run length of 8 points or more has a very low probability of occurrence in a random sample of points. Overall, therefore, there is a fair indication of statistical control.

Beyond these observations we note that data set 1 is not as critical, seeing that its maximum value is well below the USL and, in fact, all data in set 1 fall below the centre line of the specification band. Much greater attention would thus be focused on data set 2, since set 1 has no serious capability issues (White, 2021; Liu & Li, 2021).

Data set 2

The picture for the second data stream (Figure 7) is slightly different from set 1, with one point exceeding the +/- 3 sigma limits, though falling within the specification limit.

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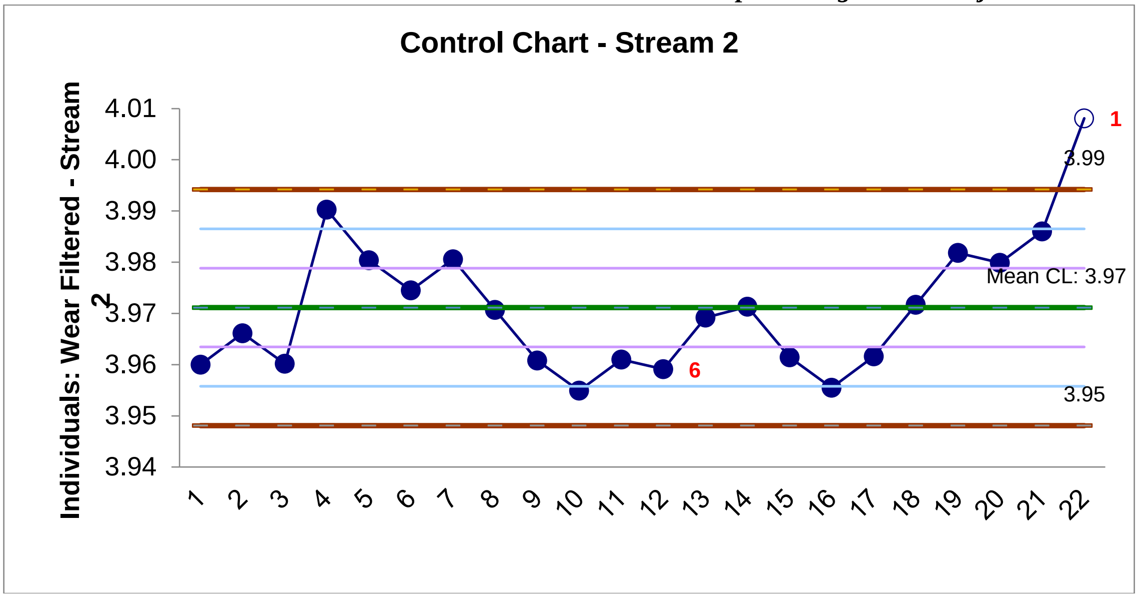

Figure 7: X-bar control chart for drawn wire diameter (Data set 2, wear filtered out)

In addition, the plotted sample averages appear to exhibit a somewhat cyclic behaviour. And since process capability analysis is applied within the normality of the process concerning defined specifications (Singh et al, 2018), a rigorous regime of performance requirements might necessitate an investigation into the normality of data set 2 even though, technically, it indicates statistical control. Nevertheless, in some ways, data set 2 shares some common features with set 1 as it portrays a roughly even distribution of points above and below the centre line, an indication of randomness (Koppel & Chang, 2016), a mitigating factor. Again, there are no big issues but unlike data set 1, the points fall on both sides of the specifications centre line even though the run-up after the 16th data point is worth paying close attention to.

Tests for special causes

Regarding the presence of special causes, we observe that for stream 1 two out of the three points 2, 4 and 11 are more than 2 standard deviations from the centre line (same side), and observation number 12 is the 4th out of 5 points that exceed 1 standard deviation from the centre line (also on the same side). For stream 2, after observation points 12 and 22, 4 out of 5 points are more than 1 standard deviation from the centre line (same side) and for observation number 22, 1 point plots more than 3 standard deviations from the centre line but these do not seem to be big issues.

The Global process - combined data

On a global scale (combined data) the overall picture (Figure 8) seems somewhat distorted, even after all the earlier corrections and transformations performed on the data. While the global process also does not seem out of control scope exists for improving its yield by eliminating or reducing the sources of local instability causing the observed non-random behaviour: the long general run-down after data point 5 is worth noting (Montgomery, 2012).

While at the level of each data set there do not seem to be any discernible runs, on a global scale there appears to be at least one. It is clear, therefore, that this distortion has to do with

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differences in scale and the wear rates of the two data streams following the merger. It would be interesting to see how a method proposed by Duro (2017) could help address this. The justification and usefulness of analysing the two data sets separately from each other is thus confirmed, even though they form an integral part of the same phenomenon. The full report is laid out in numbers in table 4 (White et al, 2021).

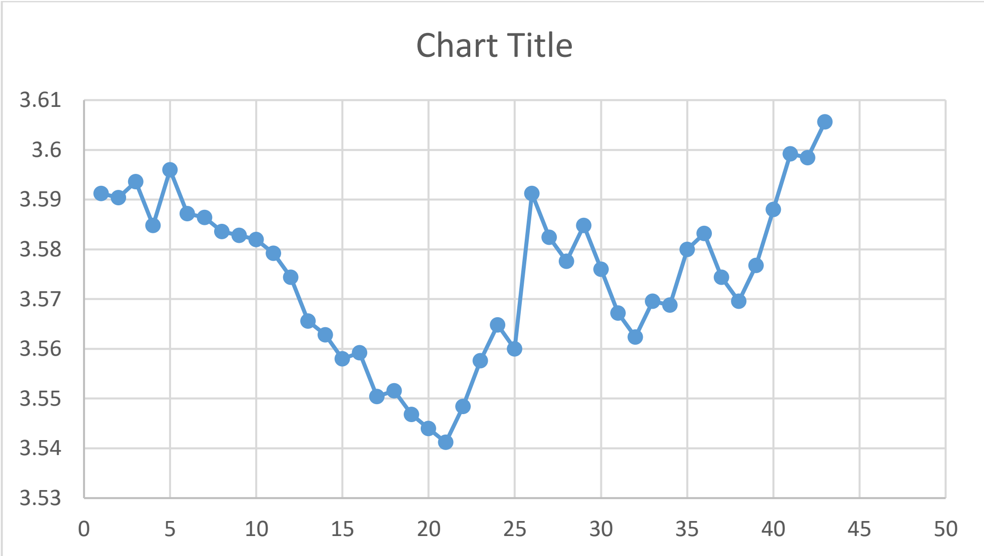

Figure 8: X-bar chart for drawn wire diameter: combined data with wear filtered out

Table 4. Process Capability Report: Wear Filtered

Statistic	**Steam 1**	**Steam 1**
Count	22	22
Mean	3.609	3.971
StDev (Short Term, Long Term)	0.003208, 0.004927	0.007687, 0.01319
USL	4.500	4.500
Target	3.600	3.960
LSL	3.600	3.960
Ppl	0.62	0.28
Ppk	0.62	0.28
Cpm	0.00	0.00
Cp	46.75	11.71
Cpu	92.56	22.93
Cpl	0.94	0.48
Cpk	0.94	0.48
ppm < LSL	32514.8	199146.4
ppm Total	32514.8	199146.4
% < LSL	3.25%	19.91%
% Total	3.25%	19.91%

Wear Management

In the present work, it seems that the part-to-part variation (that variation that would still occur if the process did not drift) is very small compared with the variation coming from the drift. In addition, this variation is nearly negligible concerning the specifications, especially in the first data set. If the process were to possess no part-to-part variation at all one could let the wire diameter grow until it reached close to the USL and then he would effect the offset (i.e. tool

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change in this context) to take the process back to the lowest dimension (QI Macros, 2022). In managing this drift, the most important index is the parts per million (ppm) or percent > USL. In this work, it is zero for both data streams.

Differentiation

Novelties in the present work include:

a. It enables data from a one-sided process to be treated as though they are two-sided, with the potential to reveal useful and significant features, e.g. observations falling below the minimum die size.
b. For such data, the *Centre Line* could be treated as a target if the external specification was two-sided. Then a point plotting 3-sigma above or below a control limit would not necessarily imply the process is out of control.
c. The methodology helps to differentiate the two variations (the part-to-part and the expected trend) in an easy, more transparent, and insightful manner, thus aiding the analysis.
d. By regimenting the analysis of otherwise non-normal global data, the Box-Cox transformation with its accompanying change of specification limits can be avoided if each regiment turns out normal, as it did in this work.
e. Out-of-control occurrences outside of the trend have a far greater chance of being exposed for action.
f. If the steady trend is not intrinsic, i.e. where the drift can be eliminated, the methodology provides us with a very effective means of tracking "behind-the-scenes" developments while offsets are being used to manage the drift temporarily until it is eliminated through the identification of assignable causes and taking action on them.

CONCLUSION

Owing to the nature of the nail manufacturing process where the wire is drawn through a series of dies, these dies are subject to progressive wear, resulting in a continuous upward drift in the mean diameter of the drawn wire. If not treated specially, this natural (inherent) drift would interfere with the statistical analysis of data with the risk of clouding any out-of-normal patterns in the data that might hold important information about the process. Based on these considerations and the discussions in section 4.0, the following conclusions can be drawn:

1. The process analysed in this study is in statistical control with the part-to-part variations small compared with the specification.
2. Filtering out a natural trend from data does not preclude the possibility of other assignable patterns. In the particular case of this study, other trends (albeit, minor and probably unrelated to tool wear) were found present, and assignable causes were needed to address these patterns.
3. The results of the study are somewhat self-validating: Any observations falling below the minimum diameter of 3.6 mm (Data set 1) could be due to inconsistencies in the size of the finishing die-opening or even measurement errors.
4. Filtering natural trends from data gives satisfactory results and is thus appropriate for tracking continuously drifting processes both intrinsic and otherwise.

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REFERENCES

Aravind, S., Shunmugesh, K., & Akhil, K. T. (2017). Process Capability Analysis and
Chalisgaonkar, R., & Kumar, J. (2014). Process capability analysis and optimization in WEDM of commercially pure titanium. *Procedia Engineering*, *97*, 758-766.
de-Felipe, D., & Benedito, E. (2017). A review of univariate and multivariate process capability indices. *The International Journal of Advanced Manufacturing Technology*, *92*(5), 1687-1705.
Duro (2017) Analyze drift and shift processing of data variation during volume production. https://www.durolabs.co/blog/2017-5-23-process-shifts-and-drifts/ [Accessed Oct 13 2022].
Koppel, S., & Chang, S. I. (2016). A process capability analysis method using adjusted modified sample entropy. *Procedia Manufacturing*, *5*, 122-131.
Kumar, V., Ranjan, N., & Singh, R. (2022). Process Parametric Optimization for 3D Printing of ABS Based Multi-Structured Functional Prototypes.
Li, W., & Liu, G. (2022). Dynamic failure mode analysis approach based on an improved Taguchi process capability index. *Reliability Engineering & System Safety*, *218*, 108152
Liu, G., & Li, W. (2021). New dynamic reliability assessment method based on process capability index and fault importance index. *Quality Engineering*, *33*(1), 43-59.
Maaradji, A., Dumas, M., Rosa, M. L., & Ostovar, A. (2016, September). Fast and accurate business process drift detection. In *International Conference on Business Process Management* (pp. 406-422). Springer, Cham.
McMahon, C., & Browne, J. (1998). CADCAM: principles, practice and manufacturing management.
Montgomery, D. C. (2009). *Statistical quality control* (Vol. 7). New York: Wiley.
Ostovar, A., Leemans, S. J., & Rosa, M. L. (2020). Robust drift characterization from event streams of business processes. *ACM Transactions on Knowledge Discovery from Data (TKDD)*, *14*(3), 1-57.
Pawar, H. U., Bagga, S. K., & Dubey, D. K. (2021). Investigation of production parameters for process capability analysis: A case study. *Materials Today: Proceedings*, *43*, 196-202.
QI Macros Knowledge International Inc. Process Stability and Capability Analysis https://www.qimacros.com/lean-six-sigma-articles/process-capability-stability/ [Accessed 14 Oct 2022]
Rao, G. S., Albassam, M., & Aslam, M. (2019). Evaluation of bootstrap confidence intervals using a new non-normal process capability index. *Symmetry*, *11*(4), 484.
Saha, A., & Majumder, H. (2018). Performance analysis and optimization in turning of ASTM A36 through process capability index. *Journal of King Saud University-Engineering Sciences*, *30*(4), 377-383.
Selmi, S., Ben Amara, S., Ben Fredj, N., Kobi, A., & Ben Salah, I. (2018). Process capability indices and X $$\overline {X} $$, R control chart limit adjustments by taking into account measurement system errors. *The International Journal of Advanced Manufacturing Technology*, *95*(5), 1919-1930.
Sharma, R., Singh, R., & Batish, A. (2020). On multi response optimization and process capability analysis for surface properties of 3D printed functional prototypes of PVC reinforced with PP and HAp. *Materials Today: Proceedings*, *28*, 1115-1122.

ISSN: 2408-7920

Arca Academic Publisher

Singh, R., Ahuja, I. P. S., & Grover, S. (2018). Process Capability Analysis for Frictionally Welded Dissimilar Polymeric Materials. *Materials Today: Proceedings*, *5*(9), 18502-18509.

Singh, G., Singh, R., Singh, S., Bhardwaj, A., Singh, S., & Prakash, C. (2022). Comparison of Ni-Cr based partial dentures prepared by thermoplastic and wax based investment casting: Mechanical, morphological and in-vitro analysis. *Materials Today: Proceedings*, *48*, 938-945.

Tomohiro, R., Arizono, I., & Takemoto, Y. (2020). Economic design of double sampling Cpm control chart for monitoring process capability. *International Journal of Production Economics*, *221*, 107468.

White, K., Szarka III, J., Childress, A., & Jensen, W. (2020). A recommended set of indices for evaluating process health. *Quality Engineering*, *33*(1), 1-12.

Yeshchenko, A., Ciccio, C. D., Mendling, J., & Polyvyanyy, A. (2019, November). Comprehensive process drift detection with visual analytics. In *International Conference on Conceptual Modeling* (pp. 119-135). Springer, Cham. [Accessed Oct 13 2022]

Zheng, C., Wen, L., Wang, J. (2017): Detecting process concept drifts from event logs. In: OTM CoopIS, pp. 524–542.