



### RESEARCH ARTICLE

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## ZERO-DEFECT MANUFACTURING IN THE INDUSTRY 4.0 ERA: A HYBRID APPROACH TO DETECTING QUALITY SHIFTS

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### ABSTRACT

Thanks to the emergence of the Industry 4.0 paradigm, the idea of Zero-Defect Manufacturing (ZDM) has now been claimed to be possible. The ZDM is based on four strategies: detecting, repairing, predicting, and preventing. The main objective of the present work is to defend the proposition that detecting small changes in product quality is a necessary condition to prevent the generation of non-conformance and consequently implement the zero-defect concept. The traditional statistical control charts - such as the Shewhart, EWMA, and CUSUM - and a new method known as 'concept drift' were assessed as candidates to build a Decision Support System (DSS). A prototype of the designed DSS was applied to detect quality changes of tubular steering input shafts produced by end-forming. The combination of a concept drift algorithm with a Shewhart chart presented a better performance when compared to the individual behaviour of the statistical control charts.



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## I. INTRODUCTION

Modern manufacturing systems have changed significantly in recent years thanks to advances in Information and Communication Technologies (ICTs). Nowadays, cheaper and faster sensors allow data collection in real time from all the phases of the product life cycle. In this new scenario, the decision-making processes have been changing from human judgment to a data-driven approach [1],[2]. A good example of this new paradigm is the manufacturing of steering input shafts in highly automated transfer lines that can, from a lengthy tube, cut small parts, reduce its diameter, and roll threads and splines at their ends. In that kind of machine, all dimensions can be automatically controlled, and all processes - forming and measurements - are carried out without human intervention. In addition, that machinery can communicate with remote supervisory systems by means of dedicated IoT sensors [3],[4].

In that way, predictive maintenance, productivity, and quality control can be accomplished according to the Industry 4.0 paradigm. From the production phase perspective, this digital transformation has provided the necessary conditions to monitor all the material flow, including machinery and tooling. On the other hand, the physical distance to customers has apparently become shorter as the time to receive complaints has been significantly reduced. In addition, those customers supported by this more interactive relationship with the suppliers are demanding more customized products and services, thus reinforcing the so-called customer-centric business model [5]. In that new scenario, the delivery of defective products is not acceptable anymore. Moreover, it directly impacts quality cost, will cause the loss of customer goodwill, and a decline in future sales [6].

To face this problem, some researchers have claimed that the quality management systems need to be improved. Two approaches have been highlighted: Quality 4.0 and Zero-Defect Manufacturing (ZDM). Quality 4.0, digital transformation (DT), and Industry 4.0 (I4.0) are interconnected concepts [7]. In that sense, some researchers [8],[9] have argued that Quality 4.0 is a movement to update, expand, and improve the already well-founded quality management strategies - such as Statistical Quality Control (SQC), Quality Assurance (QA), and Total Quality Management (TQM) - by applying the technological resources already in use in the Industry 4.0 environment. According to [10], Quality 4.0 should not be understood just as a 'trend within a trend', as referring to the Quality 4.0 and

Industry 4.0 relationship. According to them, Quality 4.0 can be understood as “an extended approach to quality management, where recent technologies are being integrated with traditional quality practices (QC, QA, TQM) in order to expand the quality management scope and to improve quality activities’ performance and efficiency”. On the other hand, according to [11], Zero-Defect Manufacturing (ZDM) is not a new idea, but with the emergence of Industry 4.0 and its enabling technologies, the motto ‘do it right the first time’ has become possible, and the ZDM concept can now be fully implemented [12]. As both approaches can be considered I4.0 dependent and relatively new, there is not yet an explicit relationship between them in the current literature. In that line, [13] have pointed out that Quality 4.0 and ZDM are equivalent since both are considered holistic quality management approaches that make use of methods from logistics, maintenance, process control, and sustainable manufacturing.

In the current literature [12],[14-16] the ZDM concept is grounded on four strategies: detection, repair, prediction, and prevention. According to [17], prediction is an exclusive aspect of ZDM, which is absent in other quality approaches that do not learn from defects but rather eliminate them. The present paper focuses on the detection and prevention strategies of the ZDM concept, and its main objective is to defend the proposition that detecting small changes in the product quality is a necessary condition to implement the zero-defect concept in production lines. In order to achieve this goal, we assessed the isolated performance of traditional statistical methods used in statistical process monitoring - such as Shewhart, Cumulative Sum (CUSUM), and Exponentially Weighted Moving Average (EWMA) - and a more recent approach based on concept drift detection, as well as their combinations. We also propose that these methods can be applied to develop a Decision Support System (DSS) capable of detecting small changes. The conceived decision support system was applied and evaluated with real data from an automated manufacturing line dedicated to end-form tubes to make steering input shafts.

## II. METHODOLOGY

In the discrete manufacturing industry, machines are scheduled to produce individual parts by material transformations. In that scope, a change in product quality is expected to occur at any production stage. When that change happens, and its magnitude exceeds the preestablished control limits, the product will be scrapped or repaired, and the production is interrupted for corrective measures to be taken. However, if that change is within control limits, the product quality is considered satisfactory, and the machines are kept running. In the present work we argue that changes within control limits, even small, should be monitored to identify significant drifts in product quality and prevent scrap generation. Accordingly, the proposed methodology was designed based on the possibility to apply a detect-prevent strategy to achieve the Zero-Defect Manufacturing concept. The proposed methodology was conceived to support the implementation of a DSS in accordance with the requirements brought by the Industry 4.0 paradigm. Figure 1 contains the schematization of the data flowing in the DSS through three layers. The first layer contains the sensors (IoT or non-IoT) embedded into the machines.

The second layer consists of a dedicated server with data processing analytics necessary to monitor quality drifts. It is closer to the sensors. The third layer contains the same services as those provided at the second level but is far away from the shop floor. In the current literature — e.g., [2],[3],[18] — those three abovementioned layers are referred to as: edge computing (first level); fog computing (second level), and cloud computing (third level). Cloud computing has been recognized as an alternative to develop a DSS, since it reduces the impact of hardware investment and provides computing as a service [19]. However, cloud computing has some drawbacks, such as latency, bandwidth and security, compliance, and regulatory issues. Accordingly, some researchers — for example, [2],[18],[20],[21] — have proposed the fog computing approach to deal with problems demanding low response time. The DSS proposed here was designed to be implemented closer to the shop floor following the fog computing paradigm.

Nevertheless, general reports on product quality and logs of the generated events could be uploaded to the company cloud service, where relevant information can be transmitted to stakeholders. On the first level (shop floor), raw materials are transformed as they go from machine to machine until they finish as products. On each machine (or workstation) one or more characteristic is measured and its result is transferred, through a fieldbus type network to the data server on the second layer. Alternatively, and considering the possibility to install IoT sensors, the measurements can be transmitted over the HTTP (HyperText Transfer Protocol). After new data is received by the data server, the DSS processes it to detect any potential drift patterns. Four methods are proposed here to identify such drifts. The first method is the classical Shewhart control method [22], where control chart limits are determined using a technique called ‘three-sigma control limits’. This approach assumes the sample mean ( $\bar{X}$ ) as an estimator of the population mean ( $\mu$ ), and ( $\sigma$ ) as an estimator of the standard deviation. Consequently, the upper (UCL) and lower (LCL) control limits are calculated as shown in equation 1 [23].

$$\begin{aligned} UCL &= \bar{X} + 3\sigma \\ LCL &= \bar{X} - 3\sigma \end{aligned} \quad (1)$$

Second, the Cumulative Sum (CUSUM) method, as developed by Page [24], is implemented. The statistics  $C^+$  and  $C^-$  are called one-sided upper and lower cusums, and are computed according to equations 2 and 3, respectively. A process change will be detected when ( $C_i^+$ ) or ( $C_i^-$ ) surpasses the decision interval (H), as defined in equation 4. A reference (allowance) value (K) is user defined and define the shift size to be detected in relation to the target ( $\mu_0$ ). Both H and K should be chosen a priori as a multiple of the process standard deviation [23].

$$C_i^+ = \max[0, x_i - (\mu_0 + K\sigma) + C_{i-1}^+] \quad (2)$$

$$C_i^- = \min[0, x_i - (\mu_0 - K\sigma) + C_{i-1}^-] \quad (3)$$

$$UCL = H\sigma \tag{4}$$

$$LCL = -H\sigma$$

The third method utilizes the Exponentially Weighted Moving Average (EWMA), as proposed by Roberts [25]. The EWMA value ( $Z_i$ ) for an individual data point ( $x_i$ ) is calculated according to equation (5), and the UCL and LCL are determined as shown in equation (6). The smoothing parameter  $\lambda$  controls the influence of past data on the EWMA calculation, while the parameter L sets the width of the control limits and must be predefined [23].

$$Z_i = \lambda x_i + (1 - \lambda)Z_{i-1} \tag{5}$$

$$UCL = \mu_0 + L\sigma \sqrt{\left(\frac{\lambda}{2-\lambda}\right) [1 - (1-\lambda)^{2i}]} \tag{6}$$

$$LCL = \mu_0 - L\sigma \sqrt{\left(\frac{\lambda}{2-\lambda}\right) [1 - (1-\lambda)^{2i}]}$$

While the performance of these three methods has been extensively evaluated in manufacturing contexts, the detection of both abrupt and incremental quality changes remains a critical challenge for developing autonomous decision systems aimed at minimizing scrap generation in manufacturing lines. Therefore, a fourth method, ADWIN (ADaptive WINdowing), is included. ADWIN is one of several techniques developed to address the drift detection problem in supervised and unsupervised learning. This area is a dynamic research field, and a single, universally accepted algorithm has yet to emerge, as discussed in recent survey articles, e.g., [26], [27], [28], [29],[30].

Developed by [31], ADWIN inspects data streams using variable-size windows. The algorithm dynamically adjusts the window size, expanding it when no change is detected and shrinking it when data changes occur. This allows ADWIN to detect both abrupt and incremental changes with low false alarm rates. ADWIN was selected for this work due to its popularity among window-based drift detection methods [26],[29] and the availability of its code, facilitating implementation. The implementation of the third level (cloud), as schematized in Figure 1, is optional and does not impact the DSS performance. Consequently, it will not be discussed further in this work.

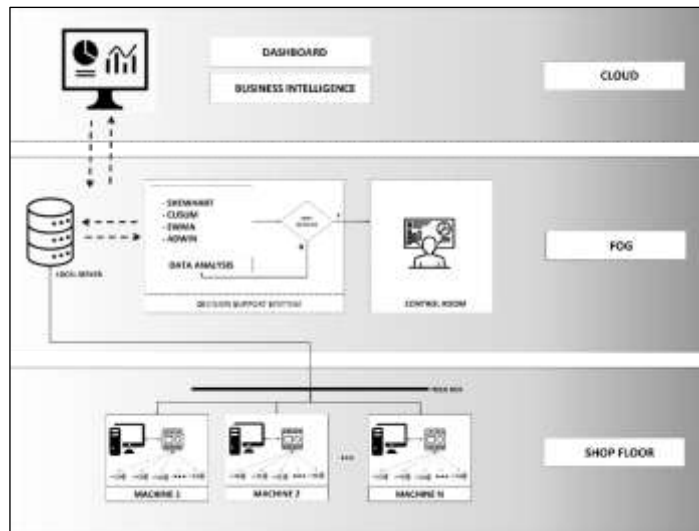


Figure 1: DSS implementation as Fog computing.  
Source: Authors, (2025).

## II.1 IMPLEMENTATION AND CASE STUDY

A DSS prototype was implemented using the Microsoft Visual Studio Community edition. The Shewhart, CUSUM, and EWMA charts were modelled directly according to equations 2 to 6. On the other hand, the ADWIN implementation was based on an algorithm coded in C++ and available in a file repository provided by Bifet [32]. The performance assessment of the prototyped DSS was carried out using real data from a fully automated production line dedicated to manufacturing tubular steering input shafts. These parts are made from long-seamed steel tubes, which are cut into smaller pieces and cold-formed at their ends to create a geometry suitable for connecting the wheel to the gearbox. After being cut into the required lengths, the tubes move through six stations where both their ends are formed and inspected. In the fourth station, a special forming operation is carried out to create a conical surface at one end of the tubes. This step is considered very critical since the length of the formed conical region limits the adjustment of the wheel in the final assembly.

Consequently, it is one hundred percent inspected by means of an automated device. Figure 2 contains a schematic view of the die and mandrel set used in the fourth station, the design tolerance for the control dimension, and the measuring device. The end-forming process is performed by a dedicated tooling (Figure 2a) which is composed of a die block (2) and two hydraulic expanding mandrels (1 and 3) responsible for forming the two ends of the tube. The measuring device is composed of four main parts: a pneumatic actuator (1), a linear guide (2), an LVDT (3), and a special jig (4) used to limit the LVDT displacement. The LVDT (Linear Variable Differential Transformer) has an analogue output and is further digitalized by a local PLC (Programmable Logic Controller) and temporally stored in a shop-floor computer. Periodically the fog server gathers and cleans this local data.

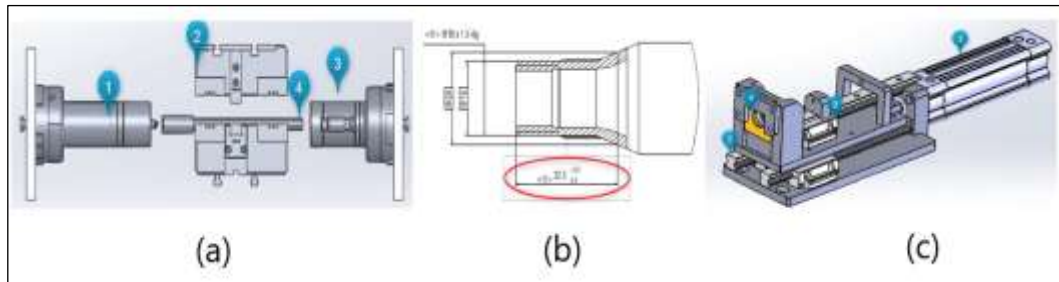


Figure 2: Mandrel and die set (a). Control dimension (b). Measuring device (c).  
Source: Authors, (2025).

The case study reported here was carried out in a multinational company with extensive experience in the field of automotive steering systems. It already has a long-standing quality control program based mainly on a visual analysis of Shewhart charts. The statistical control chart depicted in Figure 3 reflects an interval during the operation carried out in the fourth station. It can be observed that the inspected dimension lies within the control limits (UCL and LCL). If the operators notice that a new input value is plotted outside, they immediately trigger an alarm and scrap the non-conforming part. Some process parameters and the upstream operation are checked and/or adjusted to bring back the process to an ‘in-control’ state. In the case of scrap occurrences, a list of probable factors is immediately checked. The first are the outsider diameter and tube length, which were already inspected in upstream operations, but are now revised to eliminate the probable cause of the current non-conformance. Next, the temperature of the hydraulic unity is verified.

Large temperature variation affects oil viscosity and consequently the pressure and rigidity of the expanding mandrels. The die and mandrel temperatures are also important since they rise along the processing time until achieving a steady condition. However, the continuous temperature increase can be associated with significant tool wear, which affects the control dimension. The last verified item is the measurement device accuracy. It is done by measuring a standard part. Sometimes, the causes of non-conformances are not identified, and the process parameters are adjusted. The controllable process parameters are the end-forming speed and the mandrel displacement. Recently, that company has been searching for new strategies to reduce both the generation of scraps and the time/cost of identifying and correcting the process shortcomings. One of these approaches is to implement the concept of Zero-Defect Manufacturing. Consequently, the DSS designed here represents a step to accomplish this target, and its preliminary results will be presented and discussed in the following section.

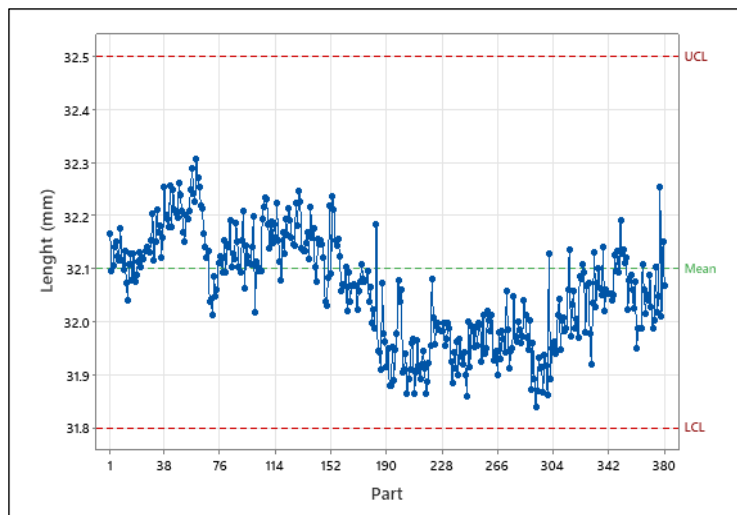


Figure 3: The control chart for a sampled interval.  
Source: Authors, (2025).

### III. RESULTS AND DISCUSSIONS

The performance of the proposed methods to detect small changes was based on historical data stored in the company fog server. In general, production is reasonably stable, and the normal distribution assumption can be accepted. Figure 4 contains the normal probability plot and a histogram, when applied on the data collected over a full day of production, which corresponds to 1457 parts.

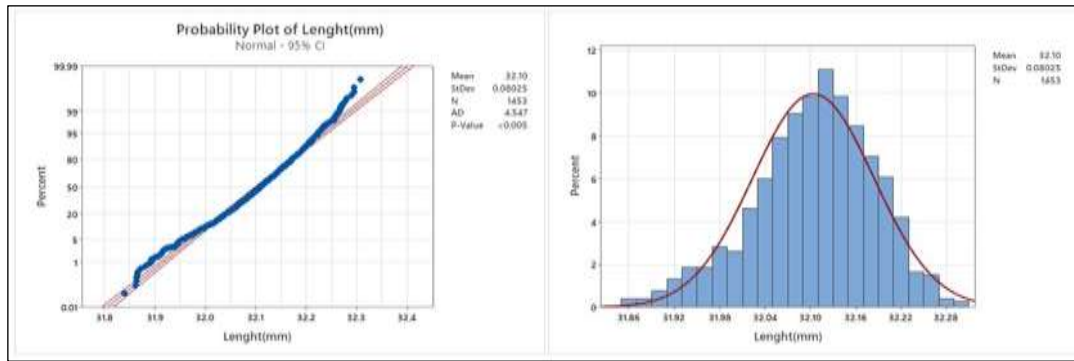


Figure 4: Normal probability plot (left) and a histogram (right) of a full production day. Source: Authors, (2025).

However, from a time-based data plotting, it can be observed that significant changes have occurred, as shown in the data stream surrounded by a blue line rectangle in Figure 5.

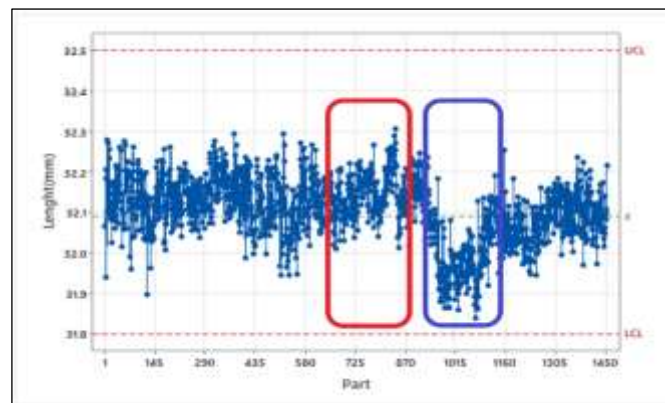


Figure 5: A sampled data stream. Source: Authors, (2025).

Figure 6 contains the results obtained after applying those three statistical techniques (Shewhart, CUSUM, EWMA) and ADWIN to part of the data stream shown in Figure 5. From the Shewhart chart (Figure 6a), the process is considered in control since none of the measurements exceed the control limits (UCL and LCL). However, both the EWMA (Figure 6b) and CUSUM (Figure 6c) charts detect a significant change in the region surrounded by the blue rectangle (Figure 5). The EWMA limits were computed by setting parameter  $\lambda = 0.2$  and  $L = 3$ , as defined in equations 5 and 6. The CUSUM intervals were calculated according to equations 2 to 4, assuming  $K = 0.5$  and the decision interval ( $H$ ) = 4. The ADWIN method (Figure 6d) was running with an initial window size of thirty measured parts. In that plot (Figure 6d), the red arrows indicate the points where small changes were detected.

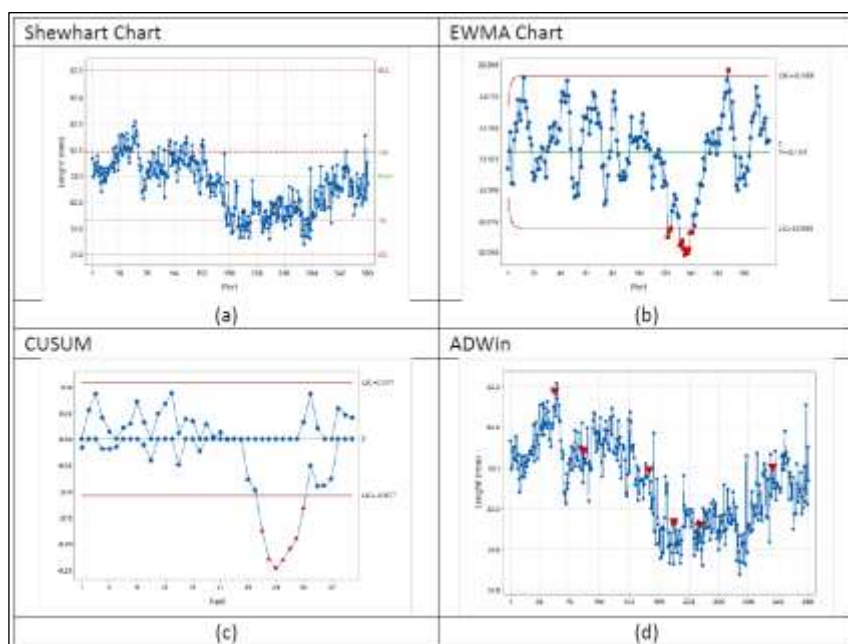


Figure 6: Change detection by statistical and concept drift methods. Source: Authors, (2025).

The false alarm rate is a very important criterion in the assessment of those methods, since a DSS that generates too many false alarms may lose its credibility. All four methods were individually evaluated over the two hundred measurements chosen from the range surrounded by the orange rectangle, as shown in Figure 5. For the CUSUM and EWMA methods, the adopted chart parameters were: CUSUM ( $0.5 \leq \mathbf{K} < 1$  and  $3 \leq \mathbf{H} \leq 5$ ) and EWMA ( $0.1 \leq \lambda \leq 1$  and  $\mathbf{L} = 3$ ). Figure 7a contains the number of false alarms for the CUSUM. It can be observed that the number of false alarms is highly influenced by the selected  $\mathbf{K}$  and  $\mathbf{H}$  parameters, but there is a comparatively larger area where this method performed very well. Both false positive and false negative alarms can be seen in some  $\mathbf{K}$ ,  $\mathbf{H}$  combinations. In a small region ( $\mathbf{K} > 0.9$  and  $\mathbf{H} > 4.77$ ), false negative alarms were registered, i. e., significant changes occurred but were not identified. The results of the EWMA method were depicted in Figure 7b.

The number of false alarms was lower than that generated by the CUSUM method, but it also was influenced by the  $\lambda$  value. Lower  $\lambda$  values render the method more sensitive for detecting smaller drifts, but they are not significant from a practical point of view and consequently results in false alarms. Shewhart's chart was dynamically calculated for every new part but keeping the buffer of the last produced parts (sample size at Figure 7c). For the smaller sample sizes there is a higher occurrence of false alarms, since the accuracy of the computed control limits is affected by the availability of data memory. The generation of false alarms was verified with the ADWIN algorithm with different window sizes (Figure 7d). It was clear that the larger the sizes of the windows, the smaller the number of false alarms. However, as observed by [33] there is a compromise between the reduction of false alarms and the speed of change detection. Consequently, we also investigated the combination of the Shewhart and ADWIN with smaller window sizes.

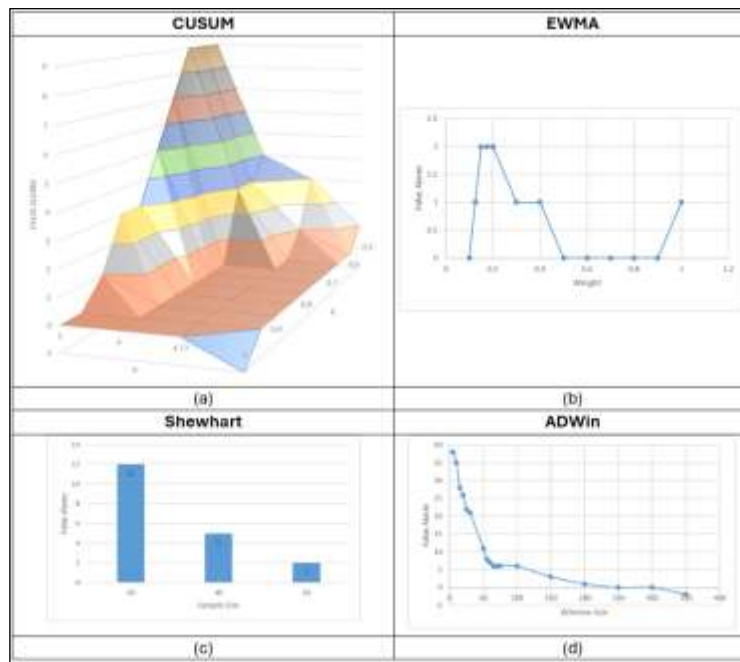


Figure 7: False alarm analysis.  
 Source: Authors, (2025).

The mixing of different control charts has been proposed in the current literature as a strategy to reduce false alarm generation [34]. Figure 8 contains the plots resulting from the ADWIN-Shewhart combination. The Shewhart limits were computed based on a buffer of 30 measured parts, and the ADWIN was computed with 10 (solid line square) and 30 (dashed line square) parts per window. Each new measured part is dynamically calculated using both methods. A small change is deemed significant if it was noticed by both the ADWIN and Shewhart methods during the same analysis window. In this case, the number of false alarms was smaller when compared to the performance of individual charts.

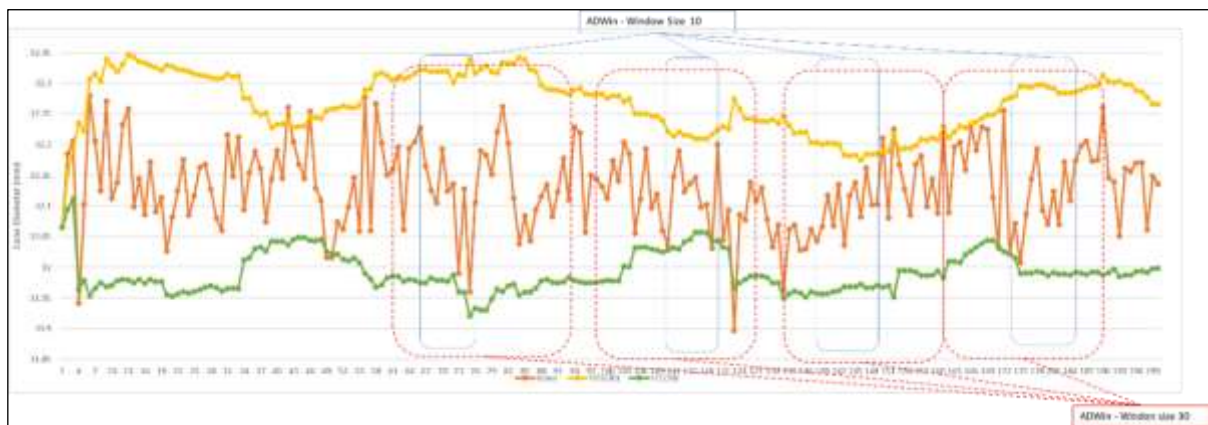


Figure 8: False alarm plots based on the ADWIN-Shewhart combination.  
 Source: Authors, (2025).

Due to the superiority of the ADWIN-Shewhart combination, it was evaluated in the processing of all gathered data depicted in Figure 5, and the result is shown in Figure 9. Significant changes were detected and confirmed at labels 1, 2, 3, and 6. A late change detection and a false alarm occurred at labels 5 and 4, respectively. The change patterns can be identified and classified - according to Gama et al. [30] - into incremental change (labels 1, 5, and 6) and abrupt change (labels 2 and 4).

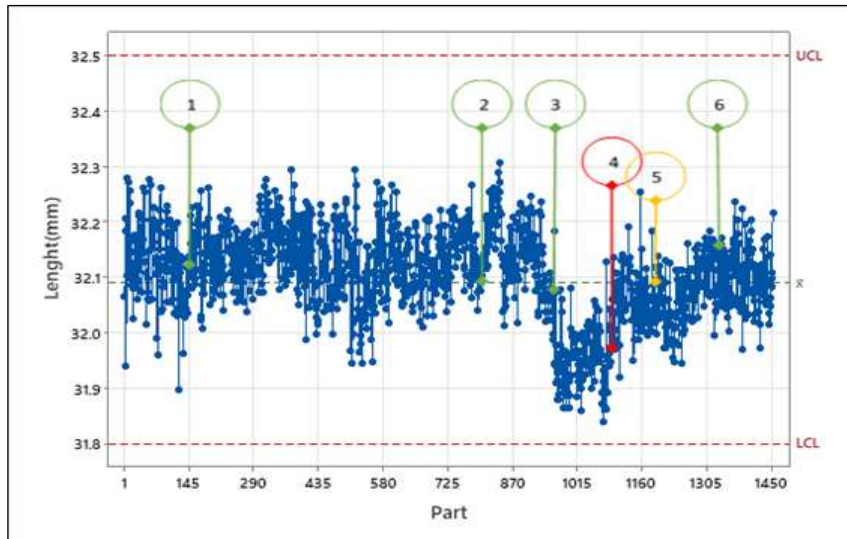


Figure 9: Evaluation of false alarms with the ADWIN-Shewhart combination.  
Source: Authors, (2025).

During the tests, the incremental change pattern was investigated and based on the engineers' previous knowledge, the formulated hypothesis was the possibility of a correlation between the die temperature and the increase in the cone length (see Figure 2b) at the tube extremity. To confirm that hypothesis, a thermocouple was installed at the external die surface next to the conical surface. Temperature was recorded simultaneously with the tube measurements, and the result is shown in Figure 10 with a reasonable coefficient of determination ( $R^2 > 0.8$ ).

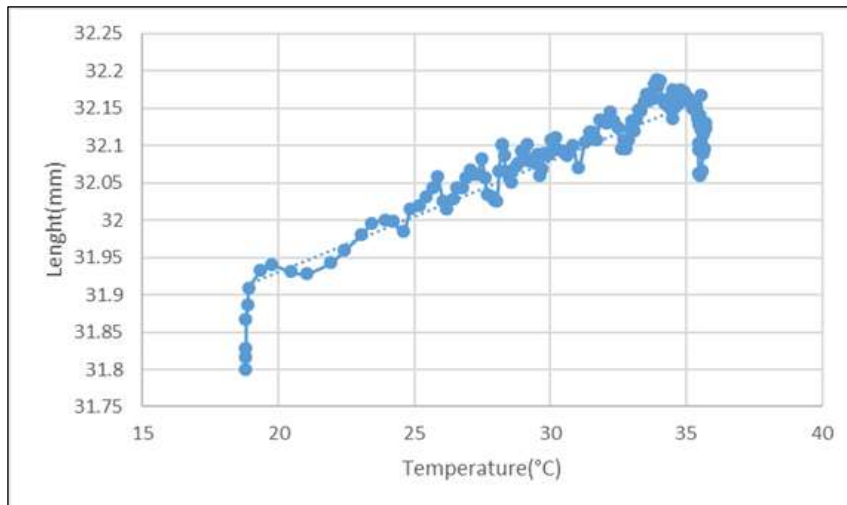


Figure 10: Correlation between die temperature and measured lengths.  
Source: Authors, (2025).

In addition to that correlation between incremental change and temperature, it was also observed that die temperature varies cyclically (cooling-heating) in very specific periods, which correspond to interruptions of the line for maintenance, shift workers, and lunch stops. The conclusion of this complementary investigation was that temperature increase affects the performance of the change detect methods until it achieves a steady state condition. Consequently, many false alarms can be expected during the die temperature increase.

To reduce the generation of false alarms, one or two heuristic strategies can be added to reinforce the change detection methods. The first is based on a parallel recording of the die temperature. The second rule considers timestamping the measured values. While the die temperature is increasing, the occurrence of an incremental change pattern of the measured values will be ignored. Similarly, the detection of incremental changes will be suspended if the elapsed time is less than necessary for the die temperature to reach a steady state.

Evidently, the inclusion of temperature and timestamp are approaches resulting from the case considered here. Nonetheless, the statistical methods, the concept drift algorithms, and the heuristics derived from a specific manufacturing process can be combined to construct a robust DSS able to detect small but significant changes and prevent scrap generation.

#### IV. CONCLUSIONS

A methodology based on statistical control charts and a concept drift algorithm was evaluated to construct a Decision Support System (DSS) able to detect small changes in product quality. The proposed system was tested with real data obtained in a fully automated production line dedicated to the end-forming of tubes used in the manufacture of steering columns. The CUSUM and the EWMA control charts were able to detect small and large quality changes, but the generation of false alarms of these methods raises a major concern, as they depend directly on their parameter settings. The combination of ADWIN - based on a 30-parts moving window - and the Shewhart chart resulted in a better detection performance able to detect changes in incremental and abrupt patterns. This combination also presented the best performance in generating false alarms when compared to the individual behaviour of the statistical control charts. Consequently, the DSS proposed here can prevent scrap generation, which is a necessary condition to implement the concept of zero-defect manufacturing. A complementary investigation revealed that die temperature impacts DSS performance in detecting incremental changes. It was observed that the recording of temperature or the timestamp data can be used as heuristic strategies to reinforce DSS performance. However, these heuristics should be understood to be very particular to the process studied here and cannot be generalized.

#### V. AUTHOR'S CONTRIBUTION

**Conceptualization:** Rafael Kovalechyn, Pablo Deivid Valle, and Dalberto Dias da Costa.

**Methodology:** Rafael Kovalechyn and Dalberto Dias da Costa.

**Investigation:** Rafael Kovalechyn.

**Discussion of results:** Rafael Kovalechyn, Pablo Deivid Valle, and Dalberto Dias da Costa.

**Writing – Original Draft:** Rafael Kovalechyn and Dalberto Dias da Costa.

**Writing – Review and Editing:** Rafael Kovalechyn, Pablo Deivid Valle, and Dalberto Dias da Costa.

**Resources:** Rafael Kovalechyn.

**Supervision:** Dalberto Dias da Costa.

**Approval of the final text:** Rafael Kovalechyn, Pablo Deivid Valle, and Dalberto Dias da Costa.

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