Statistical Process Control and Circular Economy: Challenges and Potential Applications

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***Abstract*—Stringent European Union policies, including the European Green Deal and the Circular Economy Action Plan, are exerting unprecedented pressure on member states to accelerate the adoption of secondary raw materials to meet 2030 Sustainable Development Goals (SDGs). At the same time, the Critical Raw Materials Act highlights the urgent need to improve the efficiency of resource recovery facilities, where the quality and purity of recycled outputs are critical bottlenecks. While Statistical Process Control (SPC) is a well established field in manufacturing, healthcare, and economics, its specific adaptation to the dynamic and highly heterogeneous nature of waste streams remains under-explored.**

This work presents a mini-scoping review aimed at mapping the current state of the art of SPC applications within the resource recovery sector, with special focus on sensor-based monitoring. We adhere to the PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) guidelines. Our initial search strategy queried Scopus and Web of Science for contributions published between 2021 and 2026, yielding an initial pool of approximately 6,300 records.

***Index Terms*—circular economy, quality monitoring, statistical process control**

Background and Motivation

European regulations mandate a faster transition to secondary raw materials to meet 2030 sustainability targets [1]. However, achieving these standards face the challenges of monitoring recycled materials. Unlike controlled industrial inputs, solid waste feedstock composition is highly heterogeneous, in addition, depending on the type of waste, they are prone to variability in the surrounding environmental conditions (e.g.temperature, moisture, etc.) [2], [3]. These factors lead to significant process variability that compromises the purity of recovered materials.

Various initiatives aim to enhance recovery efficiency in resource recovery facilities, ranging from advanced sorting to chemical recycling [4], [5]. For the recovery of secondary raw materials, the product requirements necessitate technological treatment measures whose type and extent are mainly determined by the origin of the waste to be sorted [6]. Here, sensor-based monitoring has emerged as a critical enabler for real-time quality control. However, industrial application of sensor-based sorting for material separation is still limited. In the field of sensor-based monitoring, optical sensors such as, RGB, Near Infrared (NIR), X-ray transmission (XRT), 3D with Laser Triangulation (3DLT) and Mid-Infrared (MIR) are used to identify and detect different materials and contaminants at high throughput. Consequently, it represents the primary frontier for real-time quality monitoring, where data acquisition is already established but often lacks rigorous statistical analysis.

SPC offers a robust framework to distinguish between natural feedstock fluctuations and genuine process faults, thereby stabilizing output quality.

This mini-scoping review aims at mapping the current state of the art of SPC in resource recovery with a special focus on sensor-based monitoring and sorting. We aim to answer two key research questions: (1) Where within the recycling value chain is SPC most critically needed to address quality control bottlenecks? and (2) What are the most effective methodologies for implementing SPC in such dynamic, heterogeneous systems? By identifying these gaps, we aim to guide the development of adaptive control strategies essential for a resilient circular economy.

Methodology

This study employs a scoping review framework adhering to the PRISMA-ScR guidelines to map the current state of statistical process control applications in resource recovery and related industrial domains [7]. An initial search across Scopus and Web of Science covering the period from 2021 to 2026 using the combined terms ”circular economy” and ”SPC” yielded minimal results, suggesting limited direct terminology alignment between these conceptual frameworks. Due to limited direct SPC applications in recycling literature, the search strategy targeted methodologically adjacent domains where similar challenges arise, including; materials science, manufacturing quality control, and sensor-based inspection systems. The objective was to identify proven SPC frameworks, sensor integration patterns, and evaluation metrics demonstrably effective under heterogeneous feed conditions, then assess their translatability to resource recovery sorting operations.

The primary search encompassed eight subject areas: Environmental Sciences (ENVSCI), Materials Sciences (MATSCIMULT), Engineering Multidisciplinary (ENGMULT), Industrial Engineering (ENGIND), Computer Science (Interdisciplinary Applications) (INTAPP), Computer Science Artificial Intelligence (CSAI), Automation and Control Systems (AC), and Manufacturing Engineering (ENGMAN). To capture sensor-based technologies relevant to sorting operations and quality assurance, targeted supplementary searches were conducted for "SPC and Computer Vision" (CVSPC) and "SPC and Spectroscopy" (SPECSPC). This multi-strategy approach ensures comprehensive capture of control-oriented literature where SPC is applied to different materials and dynamic systems. After duplicate removal across both databases, the primary search identified approximately 6,300 contributions. Additional filtering eliminated publications from unrelated disciplines including water treatment, medicine, and psychology, yielding a final corpus of 4,781 works for analysis.

TABLE I
RESULTING POOL OF PAPERS AFTER FILTERING AND DELETING DUPLICATES

Field of application	No. of publications
AC	447
CSAI	460
CVSPC	58
ENGIND	513
ENGMAN	162
ENGMULT	470
ENVSCI	824
INTAPP	412
MATSCIMULT	564
MULTSCI	615
SPECSPC	256
Total	**4781**

Data acquisition and preprocessing

Data acquisition proceeded through extraction of bibliographic records into structured Excel format organized by publication category. Each record contained article titles, abstracts, and author keywords extracted from database metadata. Prior to classification, all text fields underwent preprocessing through a cleaning pipeline wherein missing values were excluded and text from relevant columns was concatenated into unified searchable strings per article to maximize pattern detection coverage.

Pattern-Based Text Classification

The analytical framework relied on keyword-driven text mining to classify each article across five dimensions: control chart types, machine learning and deep learning methods, SPC performance metrics, optimization techniques, and sensing technologies. Five pattern dictionaries were systematically constructed through an iterative process grounded in established domain literature. Following theoretical grounding, an expansive keyword compilation phase captured acronyms, formal terminology, and informal shorthand used by authors in practice. Each candidate term underwent validation against criteria of specificity, prevalence, and potential ambiguity to balance high recall against false positive risk.

The control chart dictionary distinguished between univariate methods, time-weighted schemes, and multivariate extensions to recognize canonical implementations such as Shewhart charts alongside advanced variants like exponentially weighted moving average (EWMA) and cumulative sum (CUSUM) procedures. Particular attention was paid to model-based approaches involving principal component analysis (PCA) and squared prediction error statistics that frequently appear with dimensionality reduction techniques. The machine learning dictionary categorized algorithms along standard paradigm divisions, encompassing supervised methods like support vector machines and random forests, deep learning architectures including convolutional and recurrent neural networks, and computational intelligence techniques such as genetic algorithms and particle swarm optimization, additionally clustering methods were also included as part of unsupervised approaches (SCAN, K-means, hierarchical clustering). Acronym ambiguities were addressed through contextual rules ensuring terms referred to intended concepts when situated within modeling contexts. The sensing dictionary cataloged measurement modalities enabling data acquisition for SPC applications including spectroscopic methods such as Raman, FTIR, and near-infrared (NIR) spectroscopy as well as optical imaging systems utilizing RGB sensors, thereby linking analytical software to physical instrumentation generating data. Validation employed manual audit of a stratified random sample of fifty articles distributed across publication categories. A single reviewer classified each article using traditional abstraction methods and compared results against the automated dictionary-based extraction pipeline. Agreement between manual and automated classifications was assessed qualitatively, and discrepancies were resolved through expert review. Despite enhanced reliability, the keyword-dependent nature of this methodology imposes inherent limitations. Novel terminology not yet codified in standard literature may be overlooked and context blindness can occasionally produce misclassification when terms appear in unrelated contexts. All pattern dictionaries and source code are archived to ensure reproducibility, allowing subsequent researchers to verify classifications or extend taxonomies as the field evolves.

Category Level Aggregation

Results aggregated at two levels following per-article classification. Overall statistics pooled counts and percentages across all articles regardless of category to provide global views of methodological trends. Per-category statistics computed counts and percentages independently for each publication category to enable cross-category comparison of methodological preferences and metric usage. This dual aggregation strategy identified both dominant approaches across the full corpus and category-specific tendencies that might remain obscured in pooled analysis.

PRELIMINARY FINDINGS

The final corpus comprises 4,781 peer-reviewed articles spanning eight subject areas where SPC methodologies are actively applied. The categorization enables comparison of SPC practices across domains with varying degrees of similarity to resource recovery challenges, particularly in handling heterogeneous material streams and real-time quality monitoring.

SPC methods and control charts

This section summarizes the main results within control chart variants used in the reviewed works. Figure 1 and 2 presents results from control charts that are most commonly used across the analyzed works. On the univariate side, EWMA remains the predominant method, followed by classical Shewhart charts. In contrast, for multivariate approaches, PCA and CUSUM charts are the most frequently employed, with Hotelling's (T2) and MEWMA following as secondary options in multivariate SPC.

Shewhart-type charts dominate traditional manufacturing environments where process stability is assumed, but time-weighted methods (EWMA, CUSUM) show greater efficacy in settings with gradual drift or step-change transitions common to sorting operations. Multivariate approaches (MEWMA, T2, Q-statistics) demonstrate superior sensitivity when monitoring multiple correlated material properties simultaneously, a condition characteristic of sensor arrays measuring composition, moisture content, and contaminant levels. For instance, [8] aims at applying SPC for inter-batch contamination detection with high accuracy using two approaches based on PCA and PLS-DA. Such examples are promising for sensor based monitoring and sorting.

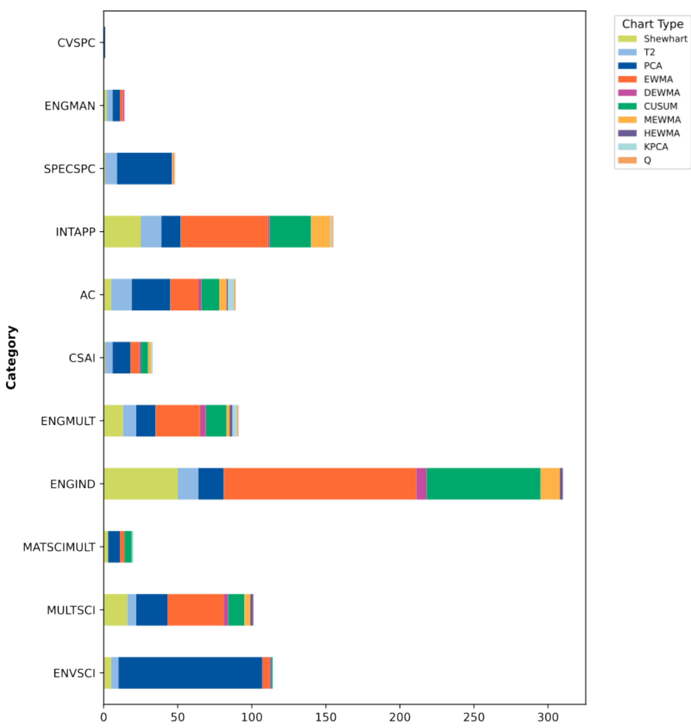

Fig. 1. Control charts application results per category.

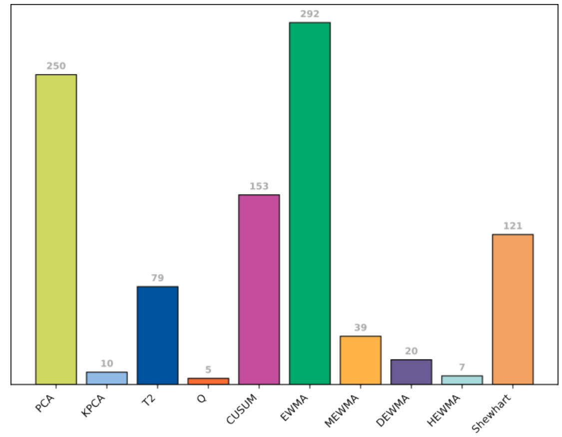

Fig. 2. Control charts application results across all categories and analyzed works.

Machine and deep learning integration

Figure 3 shows the use of machine and deep learning within the analyzed works. Machine learning methods appear in 38% of analyzed publications, predominantly serving as preprocessing layers before control chart application. Convolutional neural networks (CNNs), deep learning, facilitate classification from imaging data within the category CVSPC. Unsupervised methods including PCA and autoencoders serve dual purposes, on one side PCA is the most applied method for feature reduction within the reviewed works related to SPC. Additionally, PCA is also widely used within the works related to sensor technologies, specifically to spectroscopy.

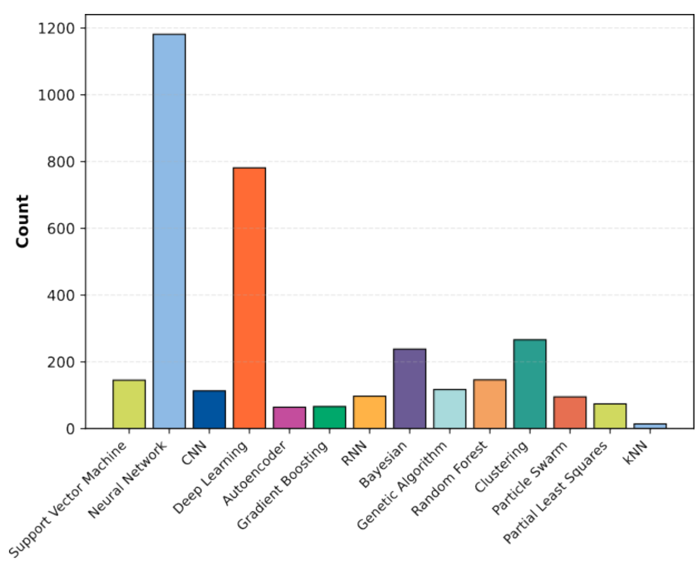

Fig. 3. Machine learning, Deep Learning application results across all categories and analyzed works.

Sensing and Instrumentation Technologies

The analysis documents fifteen sensor technology categories deployed across the corpus, with spectroscopic methods (NIR, MIR, FTIR, Raman) comprising 42% of deployments and optical imaging systems (RGB, hyperspectral, 3DLT) accounting for 31%. Figure 4 shows the distribution of the sensor technologies through the categories studied in this work. Clearly, most of the sensor technologies related works lie within the category SPECSPC.

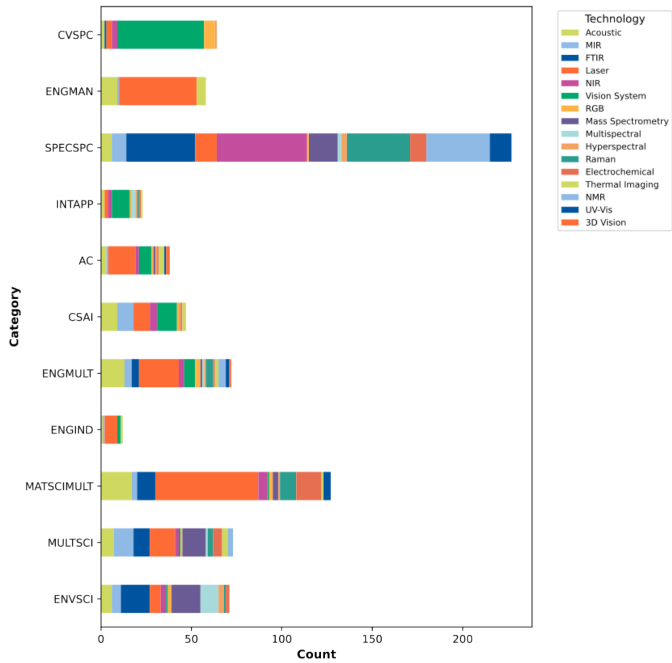

Fig. 4. Sensor technologies application results per category.

Cross-modal integration

An analysis of contributions integrating SPC with ML methods identified a total of 249 publications. As also shown in Figures 2 and 3, multivariate monitoring frameworks predominated within this subset, specifically MEWMA, PCA, and Hotelling's T2. Consistent with the complexity of high-dimensional data, Neural Networks and Deep Learning architectures emerged as the primary ML methodologies applied. Conversely, certain promising combinations show minimal representation in the literature, only 10 works apply specifically SPC and machine/deep learning in spectroscopy to analyze data quality. Particularly MIR spectroscopy only shows 1 contribution throughout the works analyzed. These underexplored intersections represent high-value targets for methodological transfer into recycling applications.

Recycling

The concept of heterogeneity in material streams presents the most significant translational challenge but at the same time, an opportunity for adapting SPC methodologies from conventional manufacturing to resource recovery. In traditional production environments, process engineers design control systems around assumptions of stationary, normally distributed variation where standard deviations remain bounded and assignable causes represent exceptional deviations from a controlled baseline. Resource recovery fundamentally violates these assumptions. Waste feedstocks exhibit non-stationary variance structures driven by seasonal collection patterns, regional consumption habits, and upstream sorting inefficiencies, producing compositional distributions that shift stourdily rather than spike transiently. This distinction means that control charts calibrated for steady-state manufacturing will either trigger persistent false alarms as natural feedstock drift exceeds static limits, or become desensitized through widened thresholds that miss genuine process degradation.

The literature analyzed in this review demonstrates that several SPC frameworks developed for comparably heterogeneous industrial contexts offer direct translational pathways. Multivariate control charts employing exponentially weighted moving average schemes (MEWMA) proved effective in chemical process industries monitoring multiple correlated quality variables subject to gradual regime shifts, a structural analog to recycling streams where polymer composition, moisture content, and contaminant loads co-vary with incoming waste batches. Particularly, [9] acknowledges high-dimensional heterogeneous processes that collect distinct physical characteristics. Ye et al. [9] integrates a sampling algorithm with a nonparametric CUSUM charts which can detect large mean shifts. [10] uses MSPC approach that considers covariate-assisted multivariate EWMA charts to detect mean shifts in the conditional distribution of process variables in view to acknowledge heterogeneous structure of in-control parameters across covariates. Other works that study heterogeneous systems also focus on data granularity, missing data, non-proportional datasets and monitoring nonstationary processes with SPC, all of which can be of great contribution to sensor-based monitoring in recycling [11]–[13]. The integration of machine learning methods with SPC frameworks further enhances transferability by decoupling monitoring sensitivity from feedstock stationarity assumptions. Deep learning architectures trained on historical sensor data can learn material-specific baseline distributions that evolve with seasonal or geographic feedstock changes, enabling dynamic recalibration of control limits without requiring explicit process models. For instance, Baek et al [14] developed an approach based on deep learning that enhanced reliability by adjusting the control limits based on the sample size and model error rate. Unsupervised methods such as autoencoders detect anomalies through reconstruction error thresholds that adapt to prevailing material compositions rather than fixed parametric assumptions. This ML-SPC hybrid approach is particularly promising for recycling applications where exhaustive characterization of every possible feedstock variant is infeasible but where anomalous contamination events must still trigger corrective actions.

CONCLUSIONS

The preliminary results from this mini-scoping review demonstrate considerable promise for the application of SPC in sensor-based monitoring within recycling plants. Notably, only a limited number of studies have explored the integration of these methods with computer vision and/or spectroscopic techniques (NIR, MIR), revealing a clear opportunity for further development at this intersection.

Importantly, the findings highlight that related fields of engineering have already developed robust methodologies for addressing challenges inherent to heterogeneous environments and dynamic systems, including anomalies such as missing data, data drift, and other forms of signal variability. These established approaches show significant potential for adaptation and transfer to the context of sensor-based monitoring in recycling, where similar data complexities are frequently encountered.

Future work should focus on extending this review through a more comprehensive and in-depth examination of the individual contributions identified, as well as the broader landscape of applicable methods. As this paper was intended to present preliminary findings, its primary aim has been to establish the foundation and motivation for such further investigation rather than to provide an exhaustive treatment of the topic.

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