mathematics

Review

Concurrent Control Chart Pattern Recognition: A Systematic Review

Ethel García, Rita Peñabaena-Niebles *, Maria Jubiz-Diaz and Angie Perez-Tafur

Department of Industrial Engineering, Universidad del Norte, Barranquilla 081007, Colombia; ethelg@uninorte.edu.co (E.G.); jubizm@uninorte.edu.co (M.J.-D.); aptafur@uninorte.edu.co (A.P.-T.)
* Correspondence: rpena@uninorte.edu.co

Abstract: The application of statistical methods to monitor a process is critical to ensure its stability. Statistical process control aims to detect and identify abnormal patterns that disrupt the natural behaviour of a process. Most studies in the literature are focused on recognising single abnormal patterns. However, in many industrial processes, more than one unusual control chart pattern may appear simultaneously, i.e., concurrent control chart patterns (CCP). Therefore, this paper aims to present a classification framework based on categories to systematically organise and analyse the existing literature regarding concurrent CCP recognition to provide a concise summary of the developments performed so far and a helpful guide for future research. The search only included journal articles and proceedings in the area. The literature search was conducted using Web of Science and Scopus databases. As a result, 41 studies were considered for the proposed classification scheme. It consists of categories designed to assure an in-depth analysis of the most relevant topics in this research area. Results concluded a lack of research in this research field. The main findings include the use of machine learning methods; the study of non-normally distributed processes; and the consideration of abnormal patterns different from the shift, trend, and cycle behaviours.

Keywords: quality control; statistical process control; concurrent patterns; machine learning

Citation: García, E.; Peñabaena-Niebles, R.; Jubiz-Diaz, M.; Perez-Tafur, A. Concurrent Control Chart Pattern Recognition: A Systematic Review. *Mathematics* **2022**, *10*, 934. https://doi.org/10.3390/math10060934

Academic Editors: Timothy M. Young and Ampalavanar Nanthakumar

Received: 15 December 2021
Accepted: 25 February 2022
Published: 15 March 2022

1. Introduction

Quality control has become an essential component of industrial processes and a key element for success in a competitive market. An effective quality-control monitoring system enables the products or services offered by a company to meet the demands of consumers. Statistical Process Control (SPC) methods are widely applied to achieve this goal. They differentiate the variability inherent in a process due to its natural behaviour from variability caused by assignable or special causes associated with an external source. The above implies that SPC methods can quickly detect when the process enters an out-of-control state and identify the abnormal process patterns related to it.

Shewhart [1] was the first author to propose the use of control charts for detecting out-of-control signals that indicate the existence of special causes that affect the process stability. Since then, many authors have developed different control charts to improve the ability to identify abnormal patterns based on two approaches. In the first approach, the analyst identifies abnormal patterns using decision rules and test zones based on training and experience once the out-of-control state is signalled. In the second, the abnormal patterns are detected and identified automatically using machine learning algorithms, such as neural networks, support vector machines, and decision trees. Between the two approaches, most studies in this area apply machine learning algorithms because of their excellent recognition rates and the advantages of automated monitoring. According to Wang et al. [2], there are 30 different control chart patterns (CCPs). Of these, eight correspond to single control chart patterns, as follows: (1) normal, (2) systematic, (3) stratification, (4) upward trend, (5) downward trend, (6) upward shift, (7) downward shift, and (8) cycle, as shown in Figure 1. The rest are concurrent patterns, i.e., the combination of single patterns.

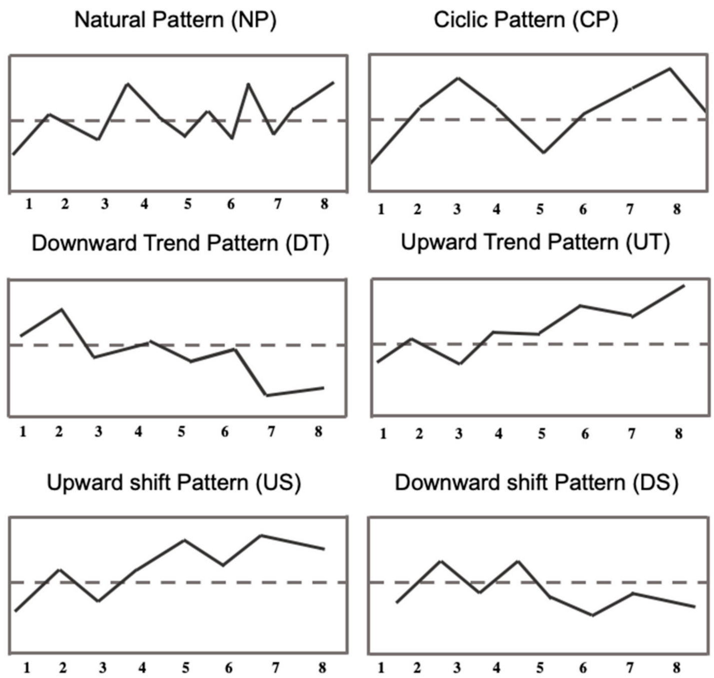

Figure 1. Examples of basic patterns in control charts [3].

There is currently a growing trend towards intelligent manufacturing systems that facilitate processes within companies. Despite their benefits, these new technologies bring challenges and change traditional solution strategies. For example, automatic monitoring provides real-time control of the state of a process but generates problems related to big data [4,5]. Likewise, pattern concurrency is increasingly common as pro- duction processes become more complex and automated [6,7]. Examples of abnormal patterns linked with manufacturing processes are operator fatigue, changes in mate-rials or equipment, periodic variation in the power supply, and tool wear [8]. Moreover, fields such as biomedicine, social media intelligence, computer vision, business analysis, retail environment, and cultural heritage are other applications of machine learning for pattern recognition [9]. However, most of the studies on CCP recognition propose methodologies based on simple CCP, even though the growing trend towards intelligent manufacturing systems forces the design of solutions involving concurrent patterns that are feasible in modern monitoring processes. When more than one pattern is present, identifying more than one pattern is a difficult task due to the interaction between several patterns and the relationship of each one with its assignable cause [10]. Therefore, dealing with the identification of CCPs by applying individual pattern recognition systems usually leads to poorer classifier performance and increases the risk associated with failing to detect when the process is out of control.

Despite the need to implement schemes to detect concurrent CCPs, the literature in this area is still limited, and new research efforts are required due to the complex nature of the problem [6,11,12]. According to Hachicha and Ghorbel [13], the paper of Guh and Tannock [14] was the first to address concurrent pattern recognition. Hachicha and Ghorbel [13] concluded that most of the reviewed articles were focused on recognizing simple CCPs arising from a single type of unnatural variation. In addition, most of the literature on SPC aimed to design control charts to identify shifts in the parameters of a quality variable. This paper provides a literature review on the concurrent recognition of CCPs, summarises the main research results, and derives helpful guidance for future research. To the authors' knowledge, this is the first review focused solely on the methodologies developed so far regarding concurrent CCP recognition. The review follows a comprehensive classification framework that distributes the studies into categories designed for an in-depth analysis of relevant topics. The analysis is performed based on a list of questions whose answers help identify the status, research gaps, and future directions for each element in this field of knowledge.

The rest of the paper is organised as follows. Section 2 describes the methodology and the proposed classification scheme. Section 3 contains the bibliometric analysis of the reviewed articles. Section 4 presents a simple descriptive statistical analysis of the obtained results, while Section 5 discusses the main barriers and challenges of this research field. Finally, Section 6 concludes the paper with the main remarks.

2. Methodology

This section details the search strategy, selection process, and bias assessment based on the PRISMA guidelines for reporting systematic reviews. PRISMA is an evidence-based set of items for developing systematic reviews. It allows for the transparent execution and documentation of the search, selection, and analysis processes. In addition, it is an iterative process that seeks to minimise the bias inherent in the authors and validates if a study provides unreliable results that affect the conclusions of the systematic review [15]. Figure 2 illustrates the identification process of studies via databases. As a result, the final subset of papers was composed of 41 papers. Each one was carefully read, and the proposed classification scheme based on research questions was applied.

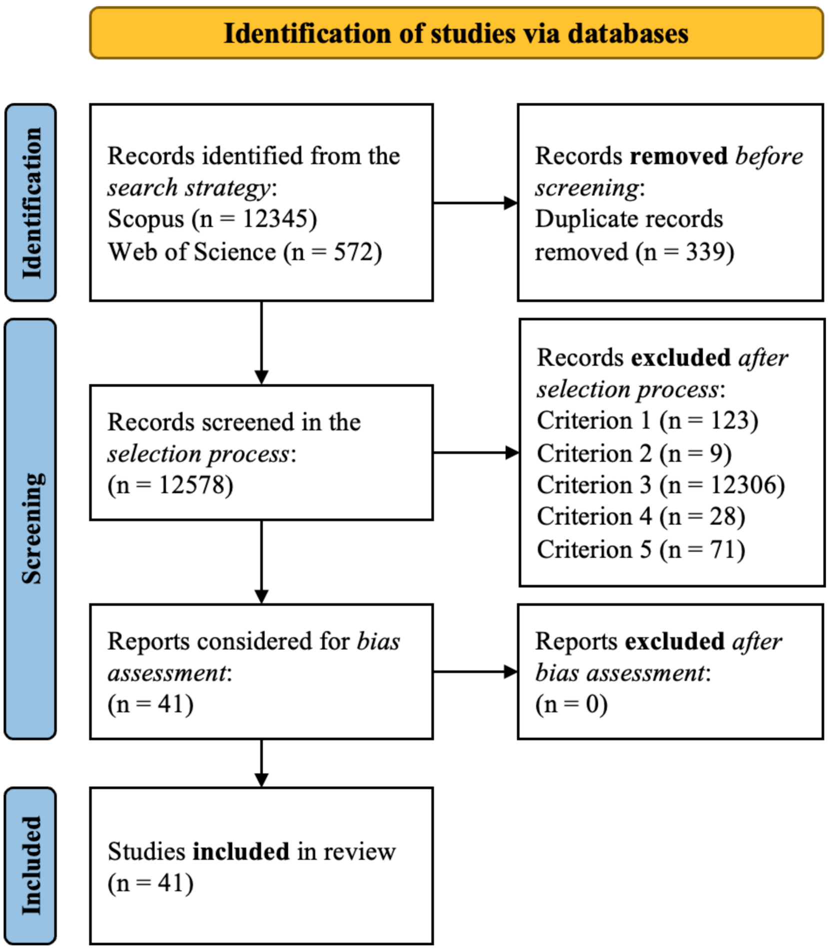

Figure 2. Identification of studies from databases.

2.1. Search Strategy

Literature on concurrent CCP recognition was searched for using the databases Web of Science (https://www.webofscience.com/wos/woscc/basic-search, accessed on 4 February 2021) and Scopus (https://www.scopus.com, accessed on 4 February 2021).

This review only considers journal articles and proceedings, i.e., it excludes unpublished scientific papers, master's dissertations, doctoral dissertations, and books. Additionally, only articles focused on engineering or computer science and pattern recognition or feature extraction were included. The search was conducted using the query ("concurrent control chart pattern" OR "mixture control chart pattern" OR "concurrent pattern recognition").

The search process provided 12,917 papers, as shown in Figure 2. The duplicated records were removed, resulting in 12,578 studies.

2.2. Selection Process

The papers that resulted from the search strategy were reviewed to include only those that fit the scope of this research. The title and abstract of each study were read and the searched articles were filtered using the following criteria:

- Criterion 1: The full text is not available in the databases.
- Criterion 2: The paper does not present a methodological approach.
- Criterion 3: The paper does not pertain to SPC problems.
- Criterion 4: The paper does not discuss a problem of CCP recognition.
- Criterion 5: The paper only addresses single CCP recognition.

It is suitable to mention that the mixed patterns presented in the Western Electrical Company [16] were not considered in this review. The authors considered these mixtures as basic patterns, although they are a combination of two. Additionally, studies focused on a simple mean and variance shift were discarded. Figure 2 shows the number of articles removed according to each criterion. A total of 12,537 papers were excluded.

Most of these were focused on behavioural patterns in humans, signals, medical variables, semiconductors, and robots.

2.3. Bias Assessment

The selected papers were submitted to a bias assessment process to determine their validity and methodological quality. This evaluation was carried out by applying the following questions:

- Is the research problem clearly defined? (Yes/No)
- Is the proposed solution clearly stated? (Yes/No)
- Does the research detail the tools applied in the proposed solution? (Yes/No)
- Are the assumptions or considerations framing the study presented? (Yes/No)
- Is the development of the solution methodology clearly explained? (Yes/No)
- Does the research have a clear definition of the main findings and results? (Yes/No)
- Are future lines of research presented? (Yes/No)

The questions were focused on the formulation of the problem, methodology, results, and proposed future research lines. A paper must have answered all questions in the affirmative for it to be included in the literature review. As shown in Figure 2, no article was excluded by this evaluation; therefore, 41 studies were finally considered for the literature review.

2.4. Classification Scheme

The classification scheme consisted of six categories whose results were subject to a comprehensive study for comparing and relating different approaches, highlighting gaps in knowledge, identifying potential future research lines, and establishing the importance of this topic within the current academic context. It was based on a list of research questions that guided the qualifying process. Thus, each answer was used for grouping the selected papers according to the proposed methodology, assumptions, and characteristics of the problem addressed. This section also contains a brief description of each question to clarify what each one covers.

A. What type of approach is used to identify concurrent CCPs? Articles are grouped according to their methodology for recognising concurrent CCPs based on their preprocessing, training, classification, and testing approaches. SP refers to a simple pattern, while CP refers to a concurrent one.

(I) Decomposition–Training SP–Classifier SP–Testing SP (Approach 1): A decomposition procedure separates concurrent patterns into simple ones. Classifiers are trained for simple pattern recognition.
(II) Training SP–Classifier SP–Testing SP/CP (Approach 2): Classifiers are trained for simple pattern recognition, and concurrent pattern classification is achieved using a threshold value. Testing evaluates both concurrent and simple pattern.
(III) Training SP/CP–Classifier SP–Testing SP/CP (Approach 3): Classifiers are designed for simple pattern recognition, and concurrent pattern classification is achieved using a threshold value. However, both training and testing procedures consider concurrent patterns.
(IV) Training SP/CP–Classifier SP/CP–Testing SP/CP (Approach 4): Classifiers are designed for both simple and concurrent pattern recognition. Both training and testing are performed with simple and concurrent patterns.
(V) Training CP–Classifier CP–Testing CP (Approach 5): Classifiers are designed for concurrent pattern recognition. Both training and testing are performed with concurrent patterns.
(VI) Statistical methods (Approach 6): The classification is performed using statistical data analysis.

B. Which classification techniques are applied? Articles are grouped according to the classification technique used to differentiate control chart patterns.

(I) Artificial neural networks (ANN): A classification algorithm inspired by the neural structures of the human brain.
(II) Decision tree (DT): A classification algorithm that separates a dataset following a branch–leaf structure.
(III) Extreme learning machine (ELM): A learning paradigm for single-hidden-layer feed-forward neural networks.
(IV) Fitted cosine curve (FCC): A technique that uses a cosine curve to decom-pose a signal into several independent components.
(V) Fitted line analysis (FLA): A technique that specialises in recognising shift and trend patterns.
(VI) Sparse representation-based classification (SRC): A technique employed for detecting active basic patterns.
(VII) Multivariate adaptive regression splines (MARS): A classification algorithm based on a divide and conquer strategy.
(VIII) Statistical correlation coefficient (SCC): A technique that uses the statistical correlation coefficient as a similarity measure to determine the pattern type.
(IX) Support vector machine (SVM): A classification algorithm that maps points in space to separate the data that belongs to different categories using a hyperplane and the largest distance between the nearest training-data points of each class.
(X) Random forest (RF): A classification algorithm that builds an ensemble of classification trees.
(XI) Rough set (RS): A classification tool for systems characterised by inexact, uncertain, or vague information.
(XII) Deep neural networks (DNN): An ANN with at least two layers.

C. What are the assumptions of the data model? This category describes the assumptions about the data model based on the nature of the process.

(I) Normally distributed data: The process data follow a normal distribution.
(II) Non-normally distributed data: In some cases, the normality assumption is not tenable, so the data are assumed to follow a non-normal distribution.

(III) (Autocorrelated process data: The variable is correlated with itself over successive time intervals.

D. What data preprocessing procedures are applied? This category groups articles according to preprocessing procedures applied to the data before the classification task.

(I) Independent component analysis (ICA): A procedure applied to separate a multivariate signal into independent subcomponents.
(II) Multi-resolution wavelet analysis (MRWA): A procedure applied to de-compose a series of data into a time–frequency space.
(III) Scaling/standardisation/codification (S/ST/CO): Methods for data scaling, standardization, and codification.
(IV) Singular spectrum analysis (SSA): A nonparametric method that decomposes a time series into a sum of components such as trends, oscillatory components, and noise.
(V) Sparse representation-based source separation (SRSS): An approach based on sparse coding.
(VI) Engineering process control (EPC): Methods applied to transform controllable variables and compensate for the effects of process disturbances.
(VII) Extreme-point symmetric mode (ESMD): An empirically-based data-analysis method that decomposes a signal into several independent components whose sum is the original signal.
(VIII) Principal component analysis (PCA): A multivariate statistical analysis method that uses linear transformation.
(IX) Second-order blind source separation (SO-BSS) techniques: Approaches applied for separating the sources, assuming that there exists a temporal correlation between the observed data.
(X) Spectral-based processing approach (SPA): method based on spectral analysis for data transformation and dimensionality reduction.
(XI) Resampling (RSA): A preprocessing method to resize an image or a signal without losing information or adding noise.

E. What type of input data is considered? Research papers are grouped according to the type of data that are fed into the classification methods to identify the pattern type.

(I) Raw data: Unprocessed input data or processed data using simple preprocessing techniques such as scaling and standardization.
(II) Extracted features: Extraction of features is performed to obtain relevant information hidden in raw data that may improve classification results.

(a) Statistical features (S1).
(b) Shape features (S2).
(c) Independent components (IC): Non-Gaussian and statistically independent additive subcomponents resulting from an ICA.
(d) SSA components (SSAC): Independent components resulting from the application of an SSA.
(e) Time–frequency localized coefficients (TFC): Time–frequency signal representations originated from a wavelet transformation.
(f) Principal component (PC): Principal components resulting from PCA.
(g) Fusion feature reduction variables (FFR): Features extracted from FFR methods.
(h) Sub-dictionary atoms (SDA): Sources resulting from SRSS methods.
(i) Engineering process control variables (EPCV): Adjusted variables resulting from EPC.
(j) Extreme-point symmetric variables (ESV): Decomposed signals resulting from ESMD methods.
(k) Second-order matrix (SOM): Unitary matrix resulting from SO-BSS.

F. Which concurrent CCPs are studied? This category classifies reviewed articles according to the concurrent control chart patterns that are subject to study.

(I) Cyclic–systematic.
(II) Shift–cyclic.
(III) Shift–normal.
(IV) Shift–systematic.
(V) Shift–trend.
(VI) Mean–variance.
(VII) Trend–cyclic.
(VIII) Trend–normal.
(IX) Trend–systematic.
(X) Stratification–normal.
(XI) Systematic–normal.
(XII) Cyclic–normal.
(XIII) Stratification–trend.
(XIV) Stratification–shift.
(XV) Stratification–cyclic.
(XVI) Stratification–systematic.
(XVII) Trend–trend.
(XVIII) Shift–shift.
(XIX) Three patterns at the same time.
(XX) Four patterns at the same time.
(XXI) Five patterns at the same time.

G. What is the evaluation approach used? This category considers whether the authors included an evaluation approach where new samples are gradually added to the analysis window, i.e., a new sample is added to the window and the oldest sample is removed.

(I) Online: The unnatural pattern appears gradually in the analysis window.
(II) Offline: The natural pattern does not appear incrementally within the analysis window; it is usually completely shown in the window.

H. What type of evaluation metrics are applied? This category considers what type of evaluation metrics were applied by the authors during the proposal construction process.

(I) Detection speed: Metrics that measure how rapidly the alternating pat tern was identified. These metrics include the out-of-control average run length (ARL_1 or ARL), average target pattern run length (ATPRL), type II error (β), average run length index (ARLIDX), average both patterns run length (ABPRL), and average time to signal (ATTS).
(II) Detection accuracy: Metrics that measure how accurate the identification of the considered patterns is; includes natural and unnatural patterns. These metrics include the classification rate (CLR), correct recognition (CR), classification accuracy (CA), recognition accuracy (RA), the percentage of correctly identified concurrent CCPs (CIC), precision (PR), recall (RE), and F1-score (F1).
(III) False alarms: Metrics that measure the identification of unnatural patterns when the process is under a natural pattern. These metrics include the false alarm (FA), in-control average run length (ARL_0), and type I error (α).

I. What type of data does the model use? This category classifies research according to the type of data used during the proposal testing process.

(I) Real data: This category groups together research that uses data obtained from the monitoring of a real process.
(II) Simulated data: This category groups research that uses data generated through established mathematical functions.

J. How is the window size determined? This category determines whether the window size is obtained through an optimisation process.
   (I) Window size analysis: Research that performed some optimisation process to select the input data window size is considered.
   (II) No window size analysis: Research that is based on other authors or establishes the window size without greater rigour is considered.
K. What is the amount of data per pattern? This category establishes whether the proposal considers an unbalanced number of patterns.
   (I) Unbalanced dataset: Research that considers the high imbalance of patterns in the actual monitoring processes.
   (II) Balanced dataset: Research that does not consider the high imbalance of patterns in the actual monitoring process.

3. Bibliometric Analysis

Several methods have been implemented to analyse the literature regarding research streams over the years. One of these is the bibliometric analysis proposed by Pritchard et al. [17]. It aims to provide a comprehensive understanding of the evolution of a research field, its boundaries, and its future directions [18]. This analysis can include authorship, keywords, affiliation, citation, co-citation, and countries; several software and tools have been used for this purpose. This section provides the bibliometric analysis of the 41 studies found via the methodology described in Section 2.

3.1. Publication Numbers

Figure 3 presents the annual production of research studies from 1999 to 2021 and the 2-year moving average for the number of publications. These indicators are relevant because they show the interest in expanding this area of knowledge. It can be observed that the years 2011, 2015, and 2020 had a concentration in the number of articles published. However, the scientific production grew from 2013 to date. Despite this slight increase, it is important to mention that the maximum number of articles published in any given year is Five. This suggests that there is still plenty of room to explore in this line of research, especially with the recent increase in the implementation of machine learning algorithms and SPC–EPC processes. In addition, the 2-year moving average shows a cycle in the publications every 5 years. This is due to the evaluation and publication times of scientific journals, especially in the ones that have few issues during a year. This phenomenon indicates the need to constantly work on research in this area of knowledge in the coming years due to the increasing automation of industrial processes that require systems of this type.

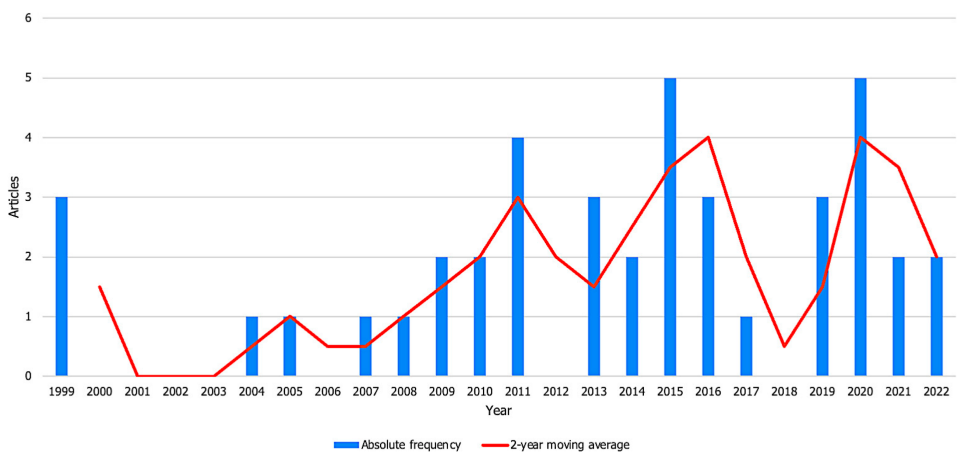

Figure 3. Number of papers published per year.

3.2. Average Citations per Year

This metric reflects the influence of published articles on subsequent research. Figure 4 shows the average number of citations that each published paper has received. Four years with peak values in this indicator can be observed in the years 1999, 2005, 2007, and 2013. However, a constancy in the citations since 2013 stands out, except for 2018, where there was no production.

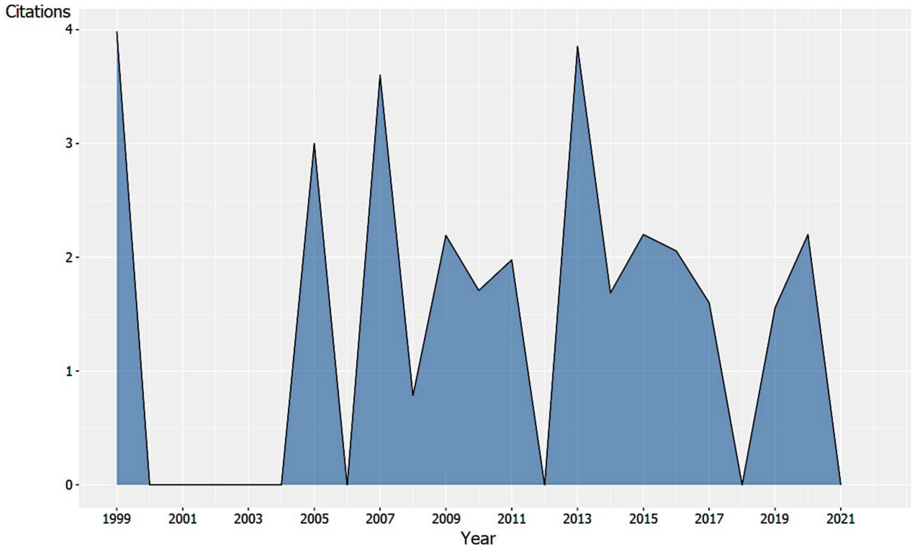

Figure 4. Average article citation per year.

The peak values are mainly due to the studies "Recognition of control chart concurrent patterns using a neural network approach" by Guh and Tannock [14], "A neural network based model for abnormal pattern recognition of control charts" by Guh and Hsieh [19], "A neural network approach to characterize pattern parameters in process control charts" by Guh and Tannock [20], "A hybrid system for SPC concurrent pattern recognition" by Chen et al. [21], "Mixture control chart patterns recognition using independent component analysis and support vector machine" conducted by Lu et al. [22], and "Recognition of concurrent control chart patterns using wavelet transform decomposition and multiclass support vector machines" by Du et al. [23]. These articles have been cited 150, 149, 110, 79, 75, and 76 times, respectively, since their publication. Since the studies developed by Guh and Tannock [14], Guh and Hsieh [19], and Guh and Tannock [20] were the first papers dealing with concurrent pattern identification in the literature, they are the basis for most of the developed research. Cited papers include studies in medicine, electronic manufacturing industry, IT services, and new systems for pattern detection in SPC–EPC processes.

3.3. Relevant Sources

Figure 5 shows the distribution of articles based on the journal in which they were published. Top four journals with the most publications are Computers and Industrial Engineering, Journal of Intelligent Manufacturing, Neurocomputing, and Lecture Notes in Computer Science (with 7, 5, 3, and 3 articles, respectively). It is important to highlight that the scope of each of these journals makes the intellectual production on this topic very concentrated in a few sources. The first three are focused on the application of methodologies mediated by technology and intelligence to solve engineering problems, while the fourth one deals with the implementation of artificial intelligence in different areas such as pattern recognition in control charts. These four journals are specialised in the topic of interest of this review. On the other hand, the remaining journals have a more general scope and so they have few publications in this research area.

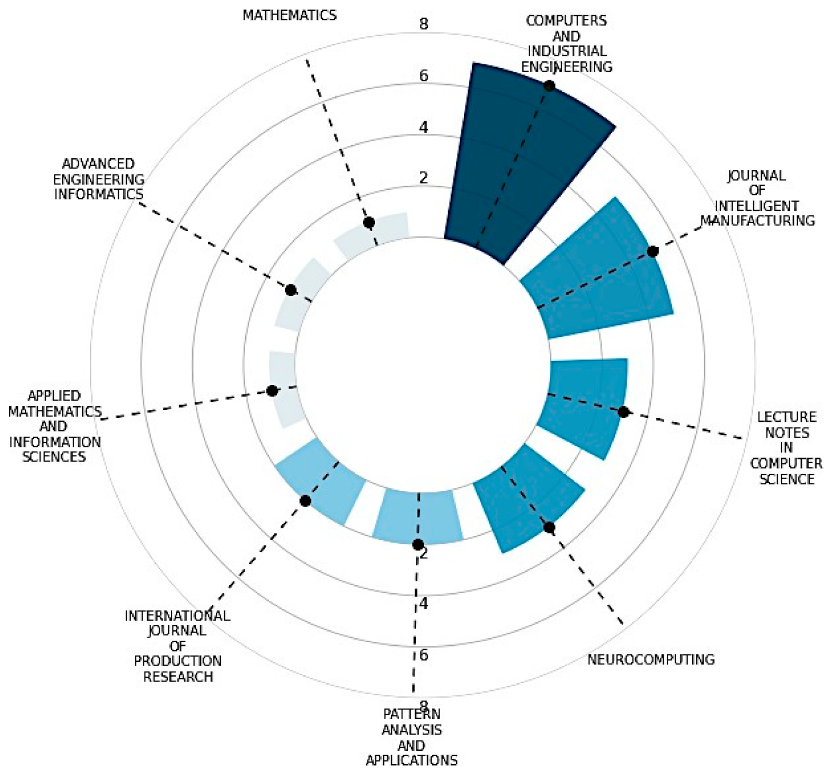

Figure 5. Journals in the field.

3.4. Country Collaboration

Another important issue is the collaboration between countries and the relationships between them aimed at developing new knowledge. Figure 6 shows the connections found between countries, and the colour of each country shows the number of publications. China is the country with the greatest presence in this area of research, followed by Iran and the United States. However, it is also noteworthy that China has published jointly with several countries such as the abovementioned ones, Australia, and Great Britain, which contributes to an increase in articles. On the other hand, there is collaboration between institutions in France and Brazil as well as directly between Australia and the United States. Unlike these countries, it can also be observed that Thailand has published on its own, that is, it has not collaborated to date. Another important issue to mention is the high contribution of European and Asian institutions in advances in this area of knowledge. On the contrary, only two countries in the Americas have published studies to date. This is largely due to the industrial development achieved by first world countries, which are at the forefront of modern technology in automated processes. In addition, it should be noted that this literature review would be the first contribution from Colombia.

3.5. Historical Direct Citation Network

Figure 7 shows the direct citation network in the reviewed papers to identify the most significant studies which have been the basis for subsequent developments. It can be observed that the works of Guh and Tannock [14] and Guh and Hsieh [19] have been cited by most of the studies published years later, even in recent research during 2021. This has occurred because they are two of the first three works in this area of knowledge, so they can be considered the starting point of this branch of research. In addition, the study published by Chen et al. [21] has also been of great influence for other studies. It should be noted that it was the first research to propose techniques for decomposing mixed patterns into simple patterns that facilitate their recognition. Other works that have also been the basis for further studies are those presented by Lu et al. [22], Du et al. [23], and Xie et al. [10].

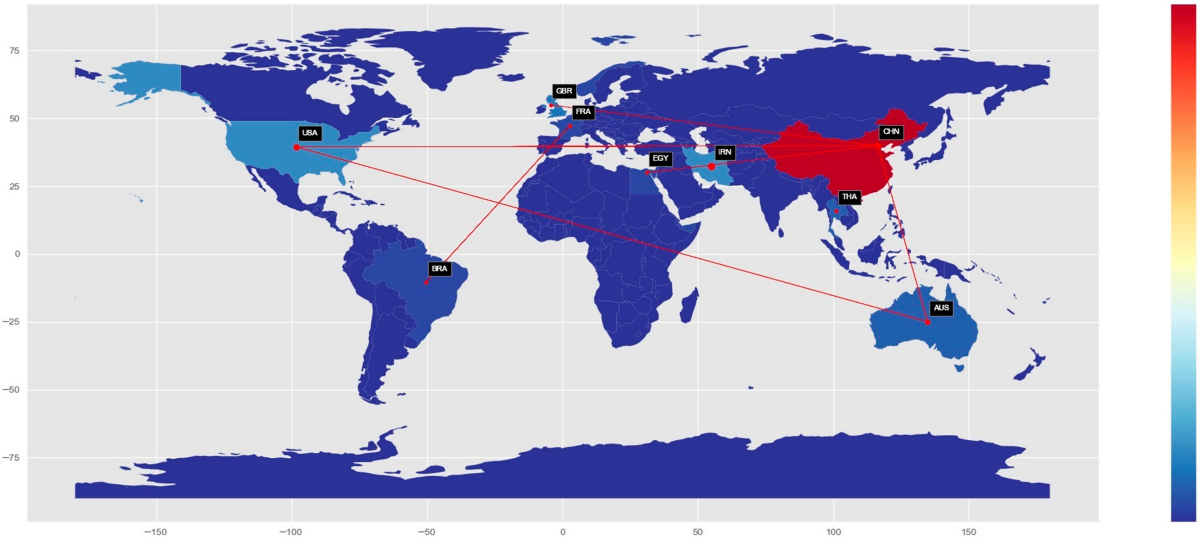

Figure 6. Country collaboration.

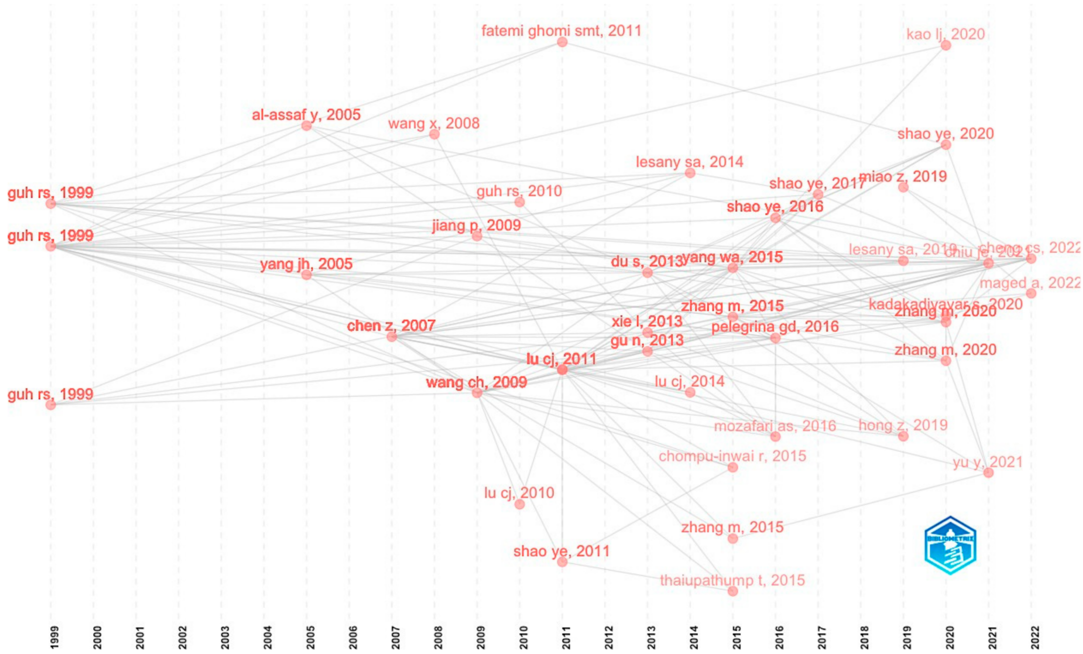

Figure 7. Historical direct citation network.

3.6. Network of Authors Keywords

Figure 8 shows the keywords with the highest occurrence in the reviewed papers. The colours indicate the clusters based on co-occurrence, i.e., keywords that are usually used together. The node size refers to the number of times each keyword has been used in the papers considered, while the connections between nodes refer to the co-occurrence between any two keywords. The keywords with the highest occurrence are “pattern recognition”, “control charts”, “statistical process control”, “flowcharting”, “control chart pattern”, “neural networks”, and “quality control”. In addition, four clusters can be identified. The red cluster shows that the words “pattern recognition”, “statistical process control”, “neural networks”, and “quality control” have a very strong co-occurrence. This occurs because neural networks are the most frequently used classification method to date for pattern recognition, as will be shown in Section 4.2. On the other hand, the green cluster reveals a strong relationship between the words “independent component analysis”, “support vector machines", and "control chart pattern", since they are techniques that are used together in several research works. The blue cluster connects the keywords related to the purpose of the articles in this systematic review, i.e., pattern recognition and SPC. Finally, the purple cluster relates the words about other methods of machine learning that have been applied for concurrent pattern recognition.

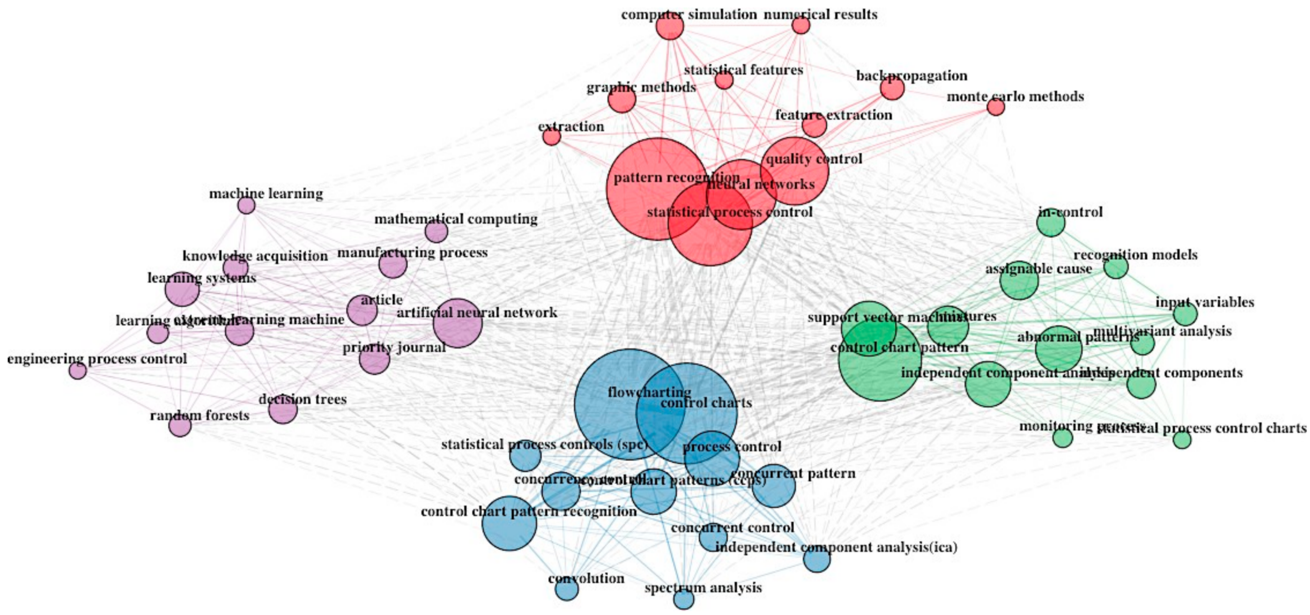

Figure 8. Network of authors' keywords.

4. Results and Discussion

The 41 reviewed articles were classified using the developed scheme presented in Section 2.4. The results for each research question are shown in Table 1. Based on the reviewed articles, a discussion is presented about the survey findings for each of the categories defined in the proposed scheme.

Table 1. Indexing of reviewed articles.

Author(s)	A	B	C	D	E	F	G	H	I	J	K
Guh and Tannock [14]	II, III	I	I	III	I	II, V, VII	I	I, II, III	II	I	II
Guh and Hsieh [19]	II	I	I	III	I	VII	II	I, II, III	II	II	II
Guh and Tannock [20]	II	I	I	III	I	VII	II	I, II, III	II	II	II
Al-Assaf [24]	II, III	I	I	II, III	II (e)	II, V, VII	II	II, III	II	II	II
Yang and Yang [25]	VI	VIII	I	-	I	II, V, VII	I	I, II, III	II	I	II
Chen et al. [21]	I	I	I	II	II (a, e)	VII	I	II, III	II	II	II
Wang [26]	II	IX	I	-	I	II, V, VII	II	II	II	II	II
Jiang et al. [27]	II, VI	I, V	I	III	I	II, V	II	II	II	II	II
Wang et al. [28]	I, VI	II, VIII	I	I	II (b, c)	I, II, IV, V, VII, IX	II	II	II	II	II
Guh [29]	III	I	I	III	III	II, V, VI, VII, XVII,	I	I, II, III, XVIII	II	II	II
Lu et al. [30]	I	IX	I	I	II (c)	III, VIII, X, XI, XII	II	II	II	II	II
Ghomi et al. [31]	IV	I	I	-	I	II, V, VII	I	I, II	II	II	II
Lu et al. [22]	I	IX	I	I	II (c)	III, VIII, X, XI, XII	II	II	II	II	II
Lu et al. [32]	I	IX	I	I	II (c)	III, VII, IX-XI,	II	II	II	II	II
						XVI-XIX					
Shao et al. [33]	I	I	I	I	II (c)	IX, XVI, XVII	II	II	II	II	II

Table 1. *Cont.*

Author(s)	A	B	C	D	E	F	G	H	I	J	K
Du et al. [23]	I, VI	VIII, IX	I	II	II (e)	II, IV, V, VII	I	II	II	I	II
Gu et al. [34]	I	I	I	IV	II (d)	I, II, IV, VII, IX	II	II	I, II	II	II
Xie et al. [10]	I	IX	I	IV	II (d)	I, II, IV, VII, IX	II	I, II	II	II	II
Lesany et al. [35]	II, VI	I, V	I	III	I	II, IV, V, VII, IX, XIX	II	II	II	II	II
Lu et al. [36]	I	IX	I	I	II (c)	I, II, IV, V, VII, IX	II	II	II	II	II
Chompu-inwai and Thaiupathump [37]	I	I, II	I	I	II (b, c)	I, II, IV, V, VII, IX	II	II	II	II	II
Thaiupathump and Chompu-inwai [38]	I	I	I	I	II (c)	I, II, IV, V, VII, IX, XVII, XVIII	II	II	II	II	II
Yang et al. [39]	I	III	I	III, II	II (j)	I, II, IV, V, VII, IX	I	I, II	II	I	II
Zhang and Cheng [40]	IV	IX	I	-	II (a, b)	II, V, VII, XIX	II	II	II	II	II
Zhang et al. [41]	IV	IX	I	VIII	II (a, b, f)	II, V, VII, XIX	II	II	II	II	II
Mozafari and Aminnayeri [42]	I	VI	I	V	II (h)	I, II, IV, V, VII, IX	II	II	II	II	II
Pelegrina et al. [3]	I	IX	I	I, IX	II (a, b, c, k)	III, VIII, XI, XII	II	II	II	II	I, II
Shao and Chiu [43]	V	I, III, X, XI	III	VI	I, II (i)	I, II, IV, V, VII, IX, XIII, XIV-XVI, XIX-XXI	II	II	II	II	II
Shao et al. [11]	IV	I, VII, IX	III	VI	I, II (i)	I, II, IV, XIX	II	I, II, III	II	II	II
Hong et al. [44]	IV	XII	I	III	I	I, II, IV, V, VII, IX	II	II	II	II	II
Lesany et al. [12]	VI	IV, V	I	III	I	II, IV, V, VII, IX, XIX	II	II	II	II	II
Miao and Yang [45]	-	XII	I	III	II (a, b)	II, V, VI	II	II	II	II	II
Kadakadiyavar et al. [46]	IV	I	I	-	I	II, V, VII, XIX	II	II	II	I	II
Kao and Chiu [47]	V	III, X, XII	III	VI	II (i)	I, II, IV, V, VII, IX, XIII, XIV, XV, XIX, XX, XXI	I	II	II	I	II
Shao and Hu [48]	IV	I, III, VII, IX	III	VI	I, II (i)	I, II, IV, XIV, XV, XVI, XIX	II	II	II	II	II
Zhang et al. [6]	IV	III	I	X	I, II (a, b, g)	II, V, VII, XIX	II	II	II	II	II
Zhang et al. [49]	IV	IX	I	VIII	I, II (a, b, g)	II, V, VII, XIX	II	II	II	II	II
Chiu and Tsai [7]	I	X	III	IV, VI	II (a, b)	I, II, IV, VII, IX, XIII, XIV, XV, XVI	I	I, II	II	II	II
Yu and Zhang [50]	IV	XII	I	III	I, II (a, b)	II, V, VII, XIX	II	I, II	II	II	II
Cheng et al. [51]	III	XII	I	III	I	II, V, VI, XX	I	II	I, II	II	II
Maged and Xie [8]	IV	XII	I	II, XI	I	II, V, VI	I	II	I, II	I	II

4.1. Concurrent Pattern Recognition Approach

As was mentioned before, this question aims to classify articles based on the approach implemented to recognise concurrent CCPs. Figure 9 shows that Approach 1 is the most used (35%), which is based on pattern decomposition and single pattern recognition. Approach 4 was found in 24% of the reviewed papers. This approach adopts statistics-based methods as a classification strategy. On the other hand, Approaches 2 and 6 were implemented in 15% and 13% of the analysed studies. The first of these uses single pattern classifiers but trains only with single patterns, while the second trains classifiers to detect concurrent patterns directly. Finally, Approaches 3 and 5 were found in 9% and 4% of the papers.

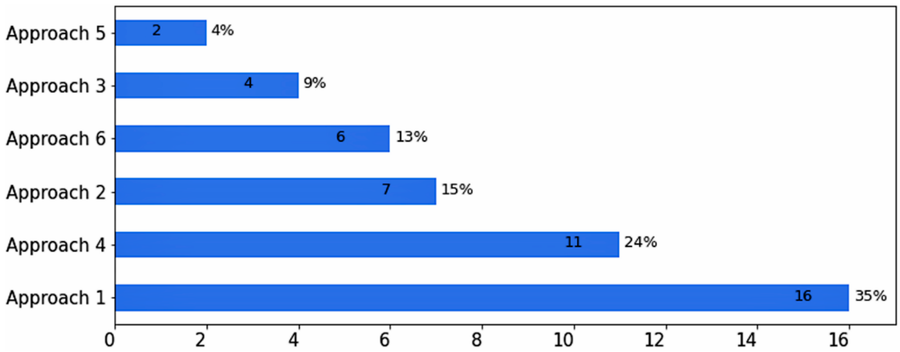

Figure 9. Breakdown of the recognition approaches.

Each of these approaches offers advantages and disadvantages. Approach 1 uses methods that not only separate concurrent patterns into single patterns but also reduce the dimensionality and eliminate noise in the data [21,23]. As a result, the classification process can be carried out using single pattern classifiers and there is no need to deal with training all pattern combination possibilities. However, one disadvantage of this approach is that it requires the implementation of decomposition techniques such as wavelet decomposition [21,23], ICA [22,28,30,36–38], SSA [7,10,34], ESMD [39], SRSS [42], and blind source separation [3]. On the other hand, Approach 4 does not need decomposition techniques. For example, Ghomi et al. [31] proposed a hybrid model that included two types of neural networks (learning vector quantization (LVQ) and multilayer perceptron (MLP)) for identifying single and concurrent CPPs. Similarly, Hong et al. [44] and Yu and Zhang [50] developed a novel convolutional neural network, while Kadakadiyavar et al. [46] presented a basis function neural network to recognise patterns. Zhang and Cheng [40], Zhang et al. [41], Shao et al. [11], and Zhang et al. [49] introduced a hybrid model in which a multiclass SVM was applied for recognising basic and mixed CCPs. Shao and Hu [48] considered ANN, SVM, ELM, and MARS techniques as classifier methods, and Zhang et al. [6] proposed a method based on kernel ELM as a classification approach. However, its major disadvantage is the greater amount of data required to train the classifier for concurrent pattern recognition; therefore, more training time is needed.

Furthermore, approaches using simple classifiers to detect concurrent patterns (Approaches 2 and 3) also have the advantage of not requiring decomposition techniques. Guh and Tannock [14], Guh and Hsieh [19], and Guh and Tannock [20] used a back-propagation network for recognising shift, trend, and cycle patterns. These patterns were also addressed by Jiang et al. [27], implementing a neural network–numerical fitting model, and Guh [29], applying a real-time ANN-based model. Al-Assaf [24] developed a monitoring system based on resolution wavelet analysis and neural networks for both single and concurrent CPPs. Wang [26] proposed a binary SVM to recognise one class pattern against others. Lesany et al. [35] developed a hybrid model in which FLA was applied for recognising shift and trend patterns, while the LVQ and MPL networks were used for identifying cyclic and systematic patterns. Nonetheless, estimating a threshold parameter is mandatory for establishing if the pattern is concurrent or not. Besides, the classification accuracy results are not the best, especially if training is only performed with single patterns [14].

On other hand, Approach 6 does not need the application of machine learning algorithms, so the training time and the complexity of the technique is reduced. For example, Yang and Yang [25] developed a pattern recognition system based on the statistical correlation coefficient method with good results for single and concurrent CPPs, while Lesany et al. [12] proposed a model based on the fitted line and fitted cosine curve methods. Although this approach is simple, it requires the selection of some decision variables as threshold values or sensitivity levels for studying significant patterns [12,39].

Finally, Approach 5 has the advantage that it does not require training the classifier with simple patterns, decreasing the amount of data and the training time associated with the algorithm. Shao and Chiu [43] evaluated the classification performance of four soft computing methods (ANN, ELM, RF, and RS), while Kao and Chiu [47] proposed a method that integrates MARS with RNN models to effectively recognise different CCPs at the same time. However, Approach 5 cannot identify single patterns. Few studies compared the performance of the approaches under the same implementation conditions. Conducting such comparisons will allow the assessment of the appropriateness of different approaches for different applications in terms of training times, amount of data required, classification accuracy, and statistical measures of performance (ARL and ATTS), among other variables of interest.

4.2. Classification Techniques

Figure 10 shows that ANNs are the predominant classification method in the literature (30%). Likewise, the results indicate similar application rates for SVM (23%); followed by the DNN method (11%); ELM method (9%); FLA, SCC, and RF methods (each one with 5%); DT and MARS methods (4%); and finally, FCC, SRC, and RS (each one with 2%).

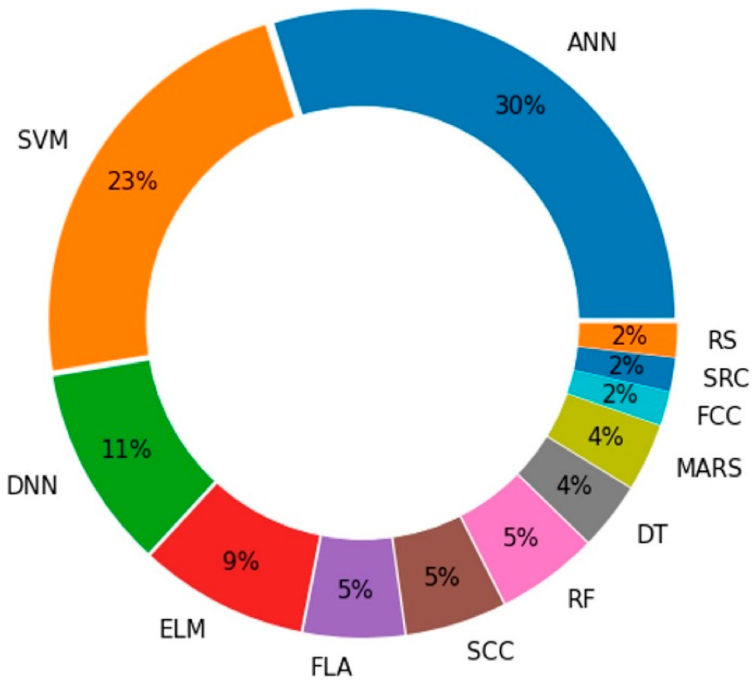

Figure 10. Breakdown of the classification techniques.

Two research trends can be identified regarding the application of classification techniques. The first trend encompasses all research efforts involving machine learning algorithms for pattern recognition such as SVM, ANN, ELM, MARS, RF, RS, and DT. The second trend encompasses all research efforts that discriminate among pattern types by applying the statistical attributes of data such as the statistical correlation coefficient method, fitted line analysis, and the fitted cosine curve.

It is important to mention that most of the studies belong to the second trend, in which statistical attributes are used with machine learning algorithms to perform the recognition task. Only the studies proposed by Yang and Yang [25] and Lesany et al. [12] are based solely on the application of statistical attributes to discriminate among patterns. These findings indicate that the application of machine learning algorithms is widely preferred for concurrent pattern recognition because of their excellent performance results. However, there is a clear dominance of ANNs among machine learning approaches, so there is ample room for a more extensive exploration of techniques such as SVM, which outperformed ANNs in a variety of applications [52]. Additionally, it would be advisable to carry out comparative studies between machine learning methods and those based on statistical attributes to establish differences in terms of performance measures as the average number of runs (ARL) or average time to signal (ATTS). The results of such studies could help determine under which circumstances it is advisable to use each method to improve overall performance.

4.3. Assumptions of the Data Model

Figure 11 shows that the authors based their research on the assumption that process data are normally distributed (78%). Only five research papers (11%) considered autocorrelated process data in their models [11,43,53]. Although the performance of control charts typically depends on the assumption of normally distributed data [54], efforts have been constantly made in the literature regarding the recognition of single control chart patterns to address process conditions in which this assumption does not hold. In the case of the literature concerning concurrent pattern identification, only Ghomi et al. [31] noted that their methodology may be extended to the case of non-normal data. Violating data assumptions commonly occurs in many real manufacturing processes, including process data that do not meet the normality assumption or the data independence assumption [55,56]. Therefore, it is important to provide alternative solutions to deal with assumption violations without jeopardising the performance of the recognition systems.

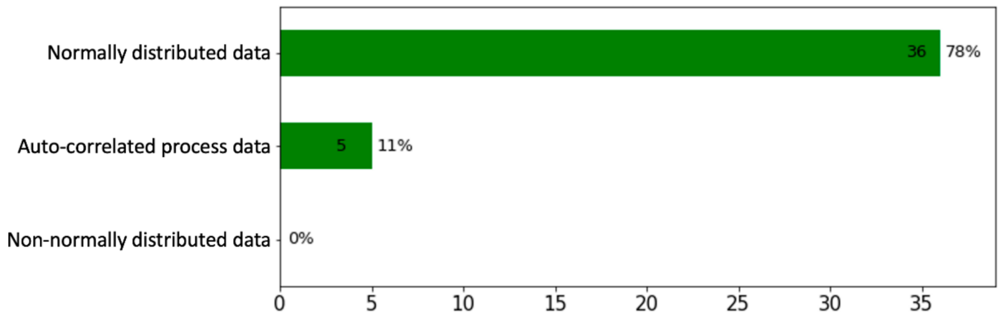

Figure 11. Breakdown of the assumptions of the data model.

4.4. Data Preprocessing Procedures

The application of preprocessing methods as a part of the concurrent pattern recognition process serves three main functions: (1) eliminating noise and reducing data dimensionality; (2) decomposing concurrent patterns into single patterns as an initial step in some recognition methodologies; and (3) adjusting a process variable to compensate for the effects of process disturbances. Figure 12 shows that techniques such as scaling, standardisation, and codification (S/ST/CO) are the most applied (32%), because they provide a fairly simple way of reducing data dimensionality, which in turn facilitates data manipulation.

On the other hand, ICA was the second most used technique among the preprocessing methods for concurrent pattern decomposition. This technique was implemented in 22% of the reviewed articles with success [28,30]. Furthermore, EPC was applied for mixed pattern decomposition in 12% of the reviewed papers [24,28,48], followed by the MRWA (10%), SSA (7%), and PCA methods (5%). SRSS, ESMD, SO-BB, SPA, and RSA were each applied for concurrent pattern decomposition in only 2% of the research papers.

Despite the benefits of these techniques as tools to facilitate and improve concurrent pattern recognition procedures, some limitations have been found associated with their application in several scenarios. For instance, wavelet-based methods entail a high computational cost when calculating the wavelet basis and require the determination of the decomposition level and the corresponding threshold for the wavelet coefficients [34]. Likewise, the application of ICA requires that the number of ICs be equal or less than the observed manufacturing process data; therefore, it is not possible to monitor univariate processes with only one key measurement. Consequently, most of the ICA applications considered noise as a source in mixtures, which is unrealistic. Additionally, inherent permutation and scaling ambiguities may result in the incorrect estimation of the sign of the recovered ICs, leading to an inability to handle concurrent patterns when the mixture consists of counterpart patterns such as UTs and DTs or USs and DSs. Besides, the performance of ICA may be compromised when handling concurrent patterns that are correlated, such as UTs and USs or DTs and DSs.

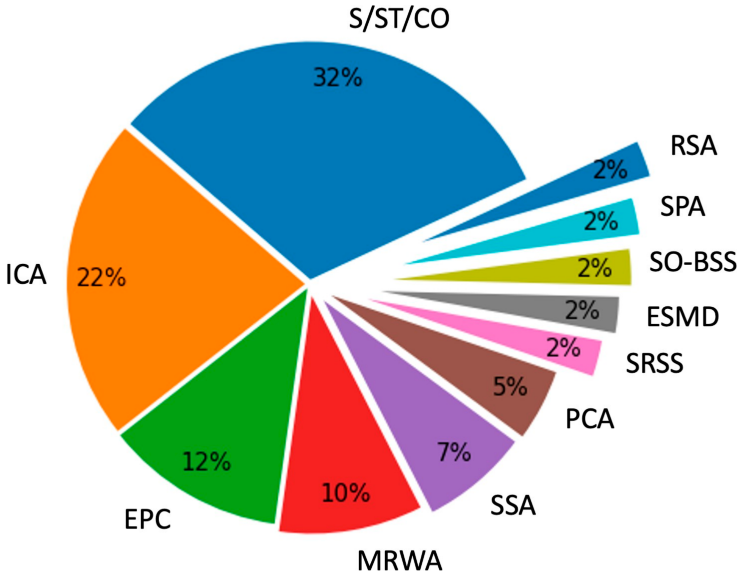

Figure 12. Breakdown of the data preprocessing procedures.

SSA does not cause any permutation and scaling ambiguity, allows decomposition with one key measurement, and requires only one parameter to be tuned. However, SSA also requires that the components are not correlated, which makes separation unfeasible for correlated patterns such as USs and UTs or DSs and DTs. Although EPC can handle uncorrelated data because of the adjustment process, its application could be more challenging than the recognition task [43]. Additionally, SRSS requires solving an NP-hard optimisation problem to determinate the number of non-zero coefficients of the input signal [42]. Unlike higher-order statistics methods such as ICA, in second-order statistics methods (SO-BSS) the sources are not described as independent and identically distributed samples. Consequently, SO-BSS is not suited for independent and identically distributed samples of a stationary distribution [3].

The main objective of PCA is to achieve the most significant information from data, reducing their complexity to a lower dimension. However, PCA presumes that the principal components with the highest variance will contain the most significant information and assumes a linear combination of the sources. Finally, estimating the error and the maximum shifting times to control the decomposing process are the principal challenges of ESMD. For the abovementioned reasons, further investigation is recommended to propose a monitoring scheme able to overcome these limitations and provide a solution for all possible monitoring scenarios.

4.5. Type of Input Data

Two main approaches are commonly used to generate input data for the classification techniques: unprocessed input data or raw data (42%); and using extracted features (58%), which include statistical features (S2), shape features (S1), or pattern components derived from decomposition techniques, as shown in Figure 13. In the literature regarding single control chart pattern recognition, feature extraction plays a crucial role in the final classification performance [57]. The advantages of using a proper set of features include the identification of more and higher CCPs, a lower execution time, complexity reduction, and overall improvement of the classification accuracy. In the case of concurrent patterns, S2, S1, and IC are the most widely used (24%, 22%, and 20% of the reviewed articles, respectively) for concurrent pattern recognition purposes. Figure 14 shows the percentage of the reviewed articles in which each extracted feature was used.

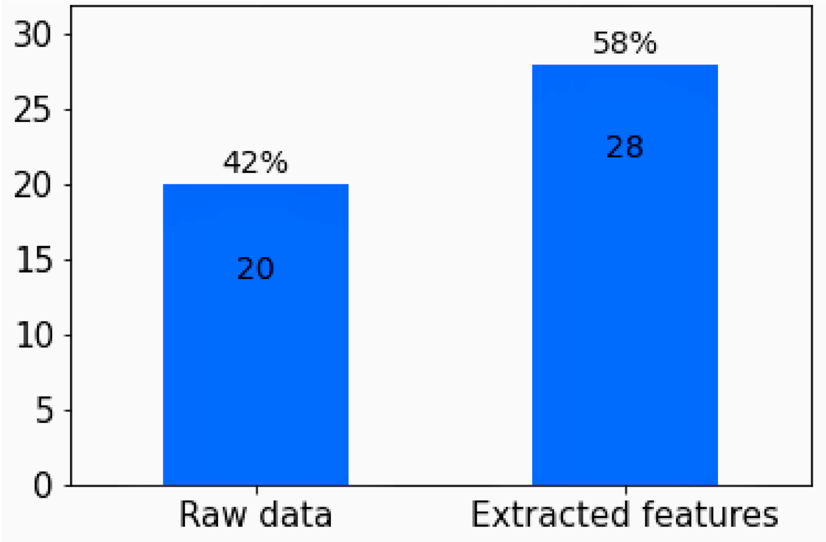

Figure 13. Breakdown of the types of input data.

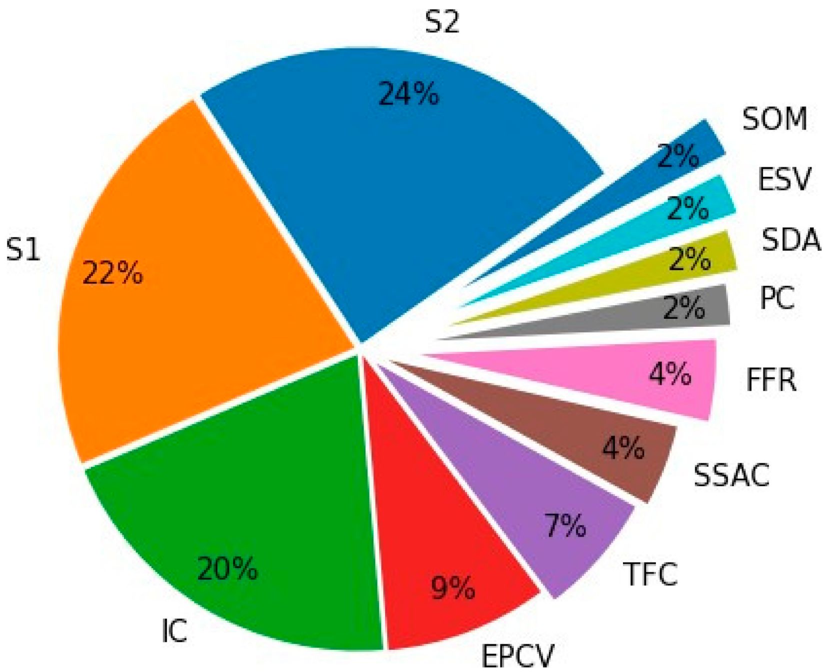

Figure 14. Breakdown of the extracted features.

There are a few research studies that integrated both statistical measures and shape properties. However, such consideration has been extensively applied as input for single pattern recognition, yielding excellent results. Therefore, it is suitable to explore the potential benefits of implementing statistical and shape features jointly for improving recognition accuracy in concurrent pattern identification systems. Moreover, few analyses aim to reduce the dimensionality and the computational complexity when original features and statistical and shape features are combined [49]. Future research may attempt to investigate these approaches.

4.6. Concurrent Control Chart Patterns Studied

Concurrent patterns can be the result of the simultaneous occurrence of different assignable causes [21,24,25]. For instance, the combination between shift and trend patterns can occur as the result of a deteriorating tool, causing a tendency in the process and the introduction of a new raw material, which causes a change in the process mean. The adequate recognition of abnormal patterns is crucial for the timely identification of assignable causes disrupting the natural behaviour of the process [25]. However, due to the interaction of more than one abnormal pattern at the same time, the detection and identification of concurrent patterns pose a higher complexity than the identification of single patterns [14]. Wang et al. [2] identified 22 different types of concurrent patterns. Figure 15 shows the most studied concurrent CCPs in the literature. Trend–cyclic (17%), shift–cyclic (17%), and shift–trend (13%) are the most widely analysed, followed by shift–systematic (10%), cyclic–systematic (8%), and trend–systematic (8%) patterns. On the other hand, research articles dealing with other mixed patterns are not common. As mentioned above, most ICA applications consider noise as a source in mixtures.

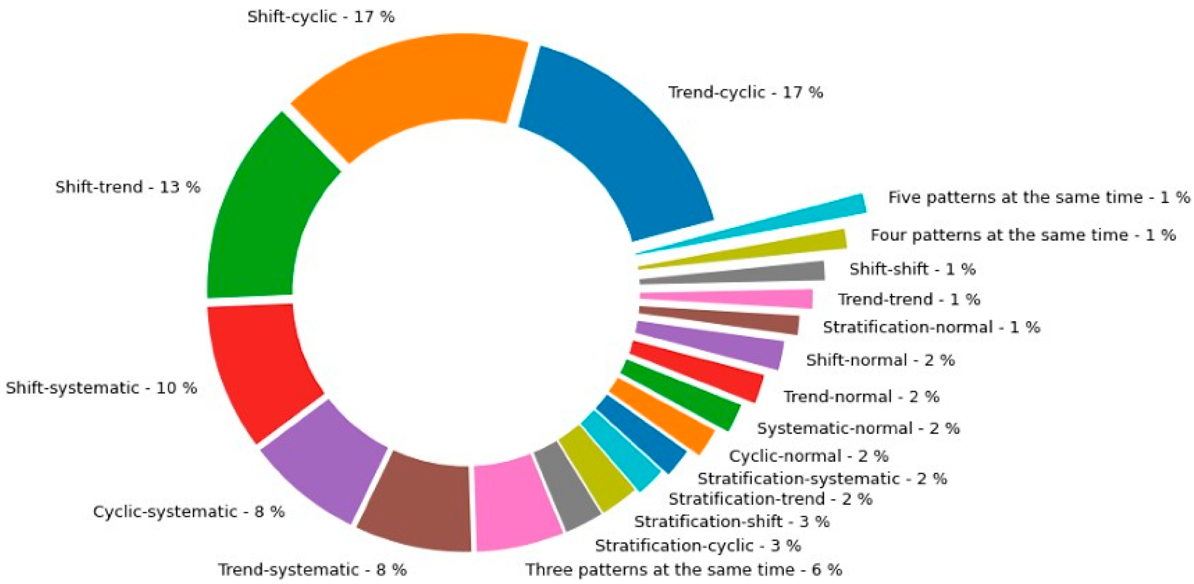

Figure 15. Breakdown of types of concurrent patterns.

Only a few research papers are concerned with the determination of the point where abnormal patterns appear in the recognition window. Pattern displacement problems may occur when the shape of patterns in the analysis window might be different from that of a prototype learned in the development stage [58]. For instance, patterns randomly appear in different parts of a recognition window as opposed to the beginning segment of the recognition window. Al-Assaf [24] found that the performance of the pattern recogniser highly depends on the location and duration of a pattern appearing in the observation window [58]. This is of great concern as single patterns occurring simultaneously are not likely to have had the same change point, and therefore neglecting the assessment of this issue may negatively affect the performance of the classification method.

4.7. Evaluation Approach

The online approach consists of monitoring a process by adding the most recent sample to the analysis window and removing the oldest sample. This strategy is the actual mechanism for monitoring processes, where unnatural patterns gradually appear in the analysis window and are difficult to identify. Authors such as Guh [59], Du et al. [60], Hachicha and Ghorbel [13], Asadi and Farjami [61], Lu et al. [62], and Chiu and Tsai [7] have highlighted the importance of considering this approach in training and testing the proposed methodology because it allows the evaluation of the speed of detection of unnatural patterns and determines the applicability of real monitoring systems [7]. Figure 16 shows the number of papers that apply an online approach and those that do not. From the total number of analysed articles, 27% apply this approach, while 73% do not. It can be observed that most of the studies addressing the identification of concurrent patterns do not consider the online approach during training and testing. In addition, most of the research papers assume a full display of the pattern within the data window, giving high accuracy but making them unfeasible for real applications [7].

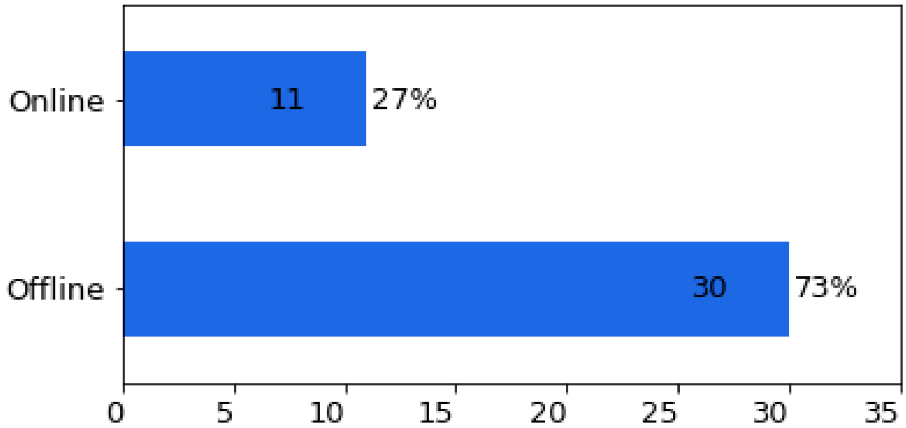

Figure 16. Breakdown of evaluation approaches.

4.8. Type of Evaluation Metrics

Figure 17 shows what type of evaluation metrics the authors applied. From the evaluated research, 69% apply metrics that evaluate the accuracy, 19% apply metrics that evaluate detection speed, and 12% consider metrics that evaluate false alarms. Applying metrics that measure accuracy allows the determination of the model's ability to correctly identify the pattern in the data window. However, applying only these metrics does not allow for a concrete conclusion about the model's performance. When monitoring real processes, the aim is to detect an unnatural pattern in the shortest possible time to reduce the costs of process failures. Therefore, it is necessary to implement speed metrics such as ARL1. For example, ARL1 allows the determination of how many samples are taken on average, once the unnatural pattern starts, to detect an alteration in the process.

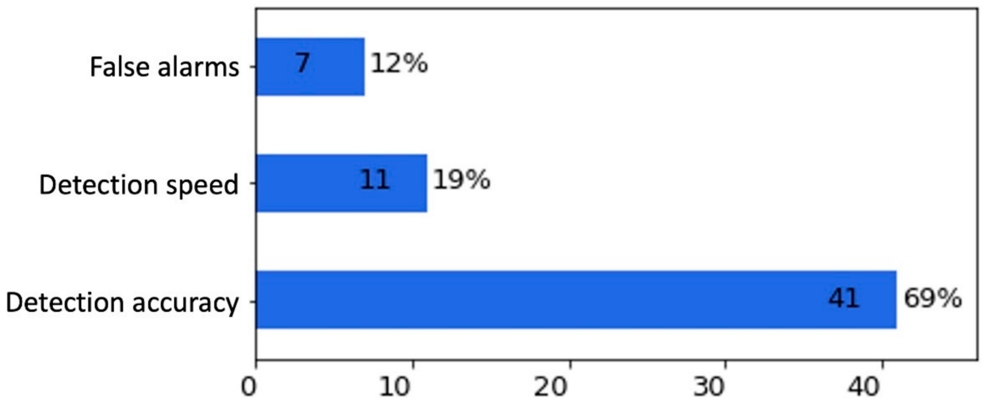

Figure 17. Breakdown of evaluation metrics.

Although speed and accuracy metrics are important, metrics focused on the number of false alarms are necessary for evaluating the implementation of models in real processes. False alarms are obtained when the process is in a steady state but a disturbance or an unnatural pattern is signalled. These false alarms result in unnecessary interruptions of production processes, generating costs associated with the search for disturbing factors that do not exist [63,64]. They are even more important when monitoring real processes because there are large periods of the natural pattern without failures, and there are much fewer periods where disturbing patterns occur. This high pattern imbalance, especially of the natural pattern, can affect the performance of a process-monitoring model [65]. Thus, research should include at least one metric that evaluates each one of these factors. If proposals that quickly detect unnatural patterns with high accuracy are desired, the number of false alarms must be as few as possible [66–68].

On the other hand, metrics to evaluate models under concurrent patterns must have special characteristics. Guh and Tannock [14] designed metrics to evaluate the performance of monitoring models considering concurrent patterns. Thus, designing comprehensive metrics that evaluate speed, false alarms, and accuracy simultaneously for concurrent patterns remains a future line of research. Most of the studies we found used only accuracy metrics, which are common to evaluate machine learning models. Only 6 authors (14% of the articles) included all three evaluation metrics. However, most of the evaluated proposals only considered false alarms during the model optimisation stage but not during the final model evaluation phase. In addition, they did not consider evaluation cases with severely imbalanced data.

4.9. Type of Data for Testing Process

Figure 18 shows what type of data was mostly used to evaluate the efficiency of the studies to date. From the evaluated research, 98% applied simulated data, while 7% implemented real data. The extensive use of simulated data to design and evaluate monitoring models can be observed. This is mainly due to the absence of fully documented public databases. For the construction of proposals, it is necessary to have data with information such as labels, change point information, or even information on the magnitude of change. Having databases with real information from monitoring processes that meet these characteristics remains a challenge for the implementation of machine learning models in the industry [69]. Only three authors included case studies with real data, which were Gu et al. [34], Cheng et al. [51], and Maged and Xie [8]. However, the real applications implemented by these authors do not represent the core of the evaluation proposal, as the latter is extensively developed with simulated data.

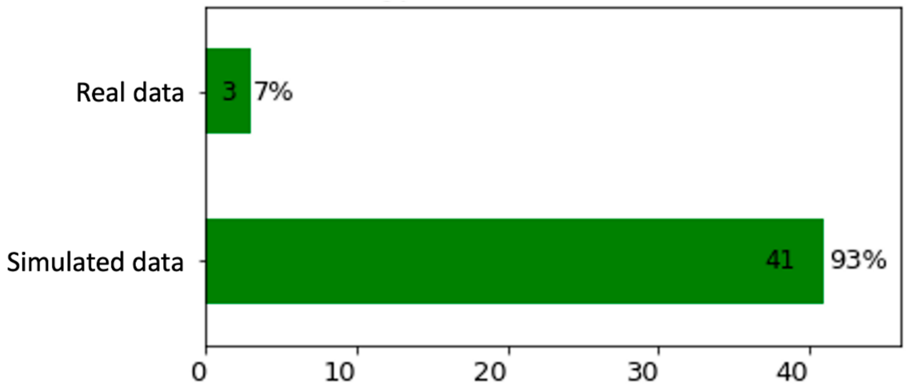

Figure 18. Breakdown of type of data for testing process.

4.10. Window Size Optimisation

The window size is known as the number of observations or samples that are analysed to determine the state of the process (steady-state or out of control). It corresponds to the raw data extracted from the monitoring process and receives preprocessing processes to generate the features that are input into the machine learning model. The window size is a key element that can affect the performance of the monitoring proposal. Authors such as Guh and Tannock [14], Guh et al. [70], Gauri and Chakraborty [71], Cheng and Ma [72], Awadalla and Sadek [73], and Cheng et al. [74] have exposed the importance of window size optimisation. Small window sizes increase the sensitivity of the model to pattern changes, i.e., it detects pattern changes faster. However, larger numbers of false alarms can be generated by having sensitive models, i.e., considering natural fluctuations as altered patterns. Conversely, large window sizes are less sensitive to changes in the pattern of the data, i.e., they are slower to detect process failures. However, they are less likely to generate non-existent alarms because they are less sensitive.

Figure 19 shows that 17% of the studies performed a window analysis and 83% did not consider this element. The window size values used in these investigations were between 16 and 64 samples. Studies that did not apply any analysis for window size selection were based on research by other authors or did not justify the value selected. Currently, some proposals attempt to take advantage of the benefits of considering small window sizes along with the benefits of applying large window sizes, e.g., Lu et al. [62] and Zan et al. [75]. These researchers consider variable window sizes that may be of evaluation interest for concurrent patterns. None of the methodologies considered this type of approach.

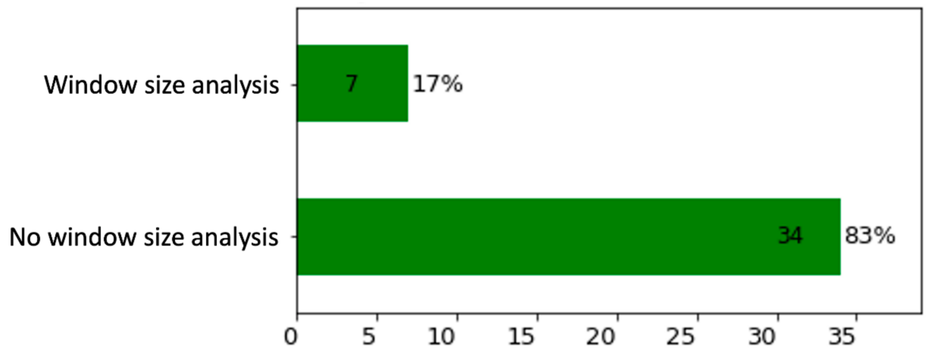

Figure 19. Breakdown of approaches for window size optimisation.

4.11. *Amount of Data per Pattern*

As mentioned, real processes are highly unbalanced. This feature can affect the performance of monitoring models by decreasing the ability to detect minority classes present in the data [76]. In this sense, if unbalanced data are not considered, models are very good at detecting certain patterns but cannot detect others. Figure 20 shows that 2% of the studies considered unbalanced data, while 98% used balanced data. The literature shows the need to apply evaluation metrics such as the G-mean, which involves both sensitivity and specificity for its calculation [77]. In addition, the application of differential weights for the most and least frequent samples in the dataset have been proposed [78].

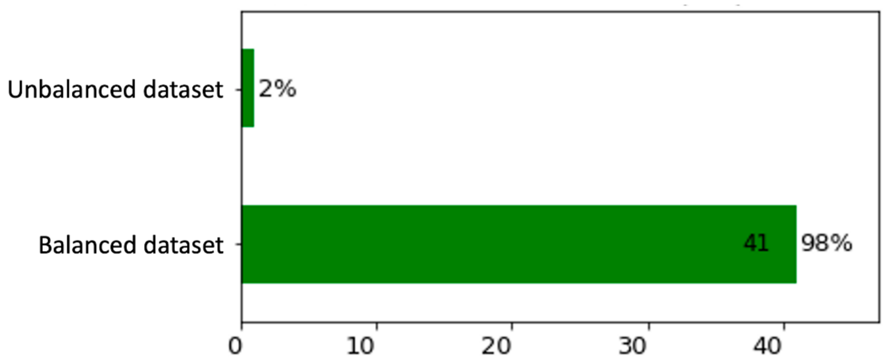

Figure 20. Breakdown of amount of data for each pattern.

5. Difficulties and Challenges for Concurrent Control Chart Pattern Recognition

Major advances in technology and big data have enabled the development of more complex manufacturing systems, where the use of sensors and automation has resulted in real-time information capture [79–81]. The above has enabled the implementation of pattern recognition techniques for fault detection of Industry 4.0 processes [82,83]. Although many authors have developed techniques for pattern recognition and have shown progress in improving process quality by increasing productivity and fault detection times, there is still a long way to go, especially in identifying concurrent patterns [81]. The mixing of one or more patterns is more common in complex and automated systems and, given the new conditions of Industry 4.0, pattern recognition research needs to consider concurrent ones [6]. However, there are still limited proposals that focus on these types of patterns.

This section presents a discussion of the difficulties encountered in the literature and the major challenges that researchers interested in concurrent pattern identification can address in upcoming studies in the area from three perspectives: (i) the design and conceptualisation of proposed algorithms or methods for pattern recognition, (ii) validation (methods) and evaluation metrics, and (iii) implementation and application.

5.1. Design and Conceptualisation of the Proposed Algorithms or Methods

The first challenge is associated with the assumptions and mechanisms used during model building. Process monitoring has become increasingly complex due to the growing automation of the industry. As a result, the data extracted to establish the state of the processes are highly unbalanced, have a large amount of noise, and form large-scale datasets [65]. In addition, another difficulty is preparing the data before the classification process, even more so when there are missing data or labelling errors [69]. Thus, research must consider these factors to develop applications that apply to the industry. Overcoming these limitations should be of high interest for future proposals for concurrent pattern monitoring. Table 2 shows the advantages and disadvantages of using different machine learning approaches.

Table 2. Advantages and disadvantages of machine learning approaches.

Approach	Algorithms	Description	Advantage	Disadvantage
Supervised	Support vector machine,	Techniques trained	Models easier to interpret	Many real problems lack
learning	artificial neural networks,	from labelled data	thanks to labels that allow	labelled data, including
	random forest, and others		performance evaluation	monitoring processes
Unsupervised	Spectral clustering,	Techniques trained	No labelled data required	Models are difficult to in-
learning	K-means, hierarchical	from unlabelled data		terpret and are sensitive
	clustering, and others			to the selected clustering
				method, i.e., methods are
				based on different distance
				or similarity metrics
Semi supervised	Transductive support	Techniques trained	Allows the building of models	Highly error-sensitive mo-
learning	vector machine, generative	from mixed data	when there are not enough	dels because they label
	models, and others	(labelled and unlabelled)	labels for a supervised model	unlabelled samples from
			labelled samples	
Deep learning	Convolutional neural network,	Technique used to auto-	Allows the building of models with	High computational requi-
	long short-term memory neural network,	matically extract complex	high volumes of data [84]	rement, computer memory
	auto encoder, and others	features from data; can be		and running time [84]
		supervised or unsupervised		

Each of these approaches represents a particular challenge for the implementation of models for monitoring real processes. Thus, only the supervised and deep learning approaches have been applied for monitoring concurrent patterns. Deep learning has gained great interest in recent years, and it is expected that future research will continue to deepen this approach due to its advantages in automated monitoring processes (high data volumes). On the other hand, although the unsupervised approach has not been explored for concurrent patterns, some proposals rely on it for simple pattern detection [85–87]. Proposing methodologies that apply unsupervised models could be the subject of future research in concurrent pattern recognition.

A common limitation in the construction of the monitoring model is the parameter optimisation process, regardless of the type of approach used. This process should not only be performed with the model's parameters but should also include the parameters of the monitoring model. Only the selection of the appropriate parameters of the machine learning model can be complex [88]. In addition, it is necessary to optimise values such as window size, sampling interval, and selection of input features, among other variables that can alter the model performance.

Likewise, existing research lacks clarity describing the training process of machine learning algorithms. Although the authors mention how many samples per pattern were used, they do not indicate how these samples are input into the model during the training process. This consideration will become more relevant if the evaluation process applies an online approach. When the unnatural pattern gradually enters the recognition window after a long period of a natural state, including various modifications to the input mechanism of the data to the network could be of interest. Some examples are an ordered training approach (like the gradual entry of the pattern into the window) or a randomised training approach (where there is no order in the distribution of the training data). Ünlü [77] proposed a training system that can serve as a basis for new proposals.

On the other hand, a clear evaluation of model scopes should be presented during the formulation of pattern monitoring proposals. The design of models that are very fast at detecting unnatural patterns but with a high number of false alarms is not applicable in real processes [66]. Authors should be more rigorous in the process of discussing results in terms of detection speed versus false alarms, even more so when processes have long periods without disturbances and false detection can generate unnecessary stoppages. Additionally, current models are not framed under a clear monitoring frequency. Real monitoring systems establish a sampling periodicity that should be optimal to detect patterns quickly, but at the same time reduce the costs associated with collecting the sample (references). This periodicity is ignored in all the analysed articles. Even when using sensors or manual sampling, this factor can determine the success of monitoring models [62]. Studying this factor is essential to ensure its applicability.

5.2. Validation and Performance Indicators

This second challenge results from the lack of a standard evaluation process to facilitate the comparative analysis of the different methodologies proposed. Currently, there are no clearly defined evaluation metrics for the comparison process, so it is necessary to define standard metrics in line with the real interest of process monitoring, i.e., to include factors such as detection speed, false alarms, and accuracy measures. Additionally, these metrics should evaluate both the overall performance of the proposal and the performance per pattern. In this way, the feasibility of each proposal per specific scenario can be identified. Authors such as Hachicha and Ghorbel [13] have highlighted the need to design specific metrics for pattern recognition control. In addition, there is no public database to evaluate the different proposals under the same testing conditions. The current testing conditions applied by the authors are not feasible for a comparative process. They test considering uncommon measures of pattern change magnitudes, different starting points of the unnatural pattern, and online and offline monitoring approaches, among others. Thus, there should be an agreement on the testing mechanism or a public evaluation database.

5.3. Implementation and Application of the Proposed Methods

The third challenge is the difficulty of implementing and applying existing methods, because the current testing mechanisms applied by many authors are not like real monitoring systems. Although it would be ideal to train and test the models using real data, there are not publicly available and known databases of real processes with documented samples at every instant during the monitoring. Simulation models can be used as an approximation to real case studies until this shortcoming is overcome. If a common database or simulation rule is established, it should consider an online monitoring approach, unbalanced patterns, and the sampling frequency during the generation of the patterns. These three components are relevant when designing models applicable to real processes. In this sense, data generation under an online approach resembles the gradual process of unnatural pattern appearance within the analysis window [7]. In addition, monitoring processes are highly unbalanced, and the testing process must take this factor into account where the frequency of the natural pattern is much higher than that of the unnatural one [65]. It is also critical to define the sampling frequency during pattern generation to evaluate under which sampling system the proposal is applicable, i.e., high-frequency online data or other systems [62]. On this approach, authors such as De la Torre Gutierrez and Pham [89] and Ünlü [77] have made proposals for generating testing standards. These two attempts are valuable in strengthening this fallacy in current research and lay the groundwork for future studies. However, they are not approaches that integrate all the points made, and thus do not guarantee the application and comparison of recognition proposals.

6. Conclusions and Future Research Lines

This paper presents a taxonomic classification of the studies developed to date focused on identifying concurrent patterns. However, this research topic can be considered relatively new and there are still gaps to be filled. In fact, there are problems that have not been solved and the proposals in the literature lack characteristics that facilitate their implementation in real processes. The proposed classification addresses key elements in the design, development, and validation of methodologies to identify concurrent patterns for SPC. In addition, a bibliometric analysis is presented showing the intellectual production over the years; important relationships between keywords, countries, and authors; and citation progress. The results of the in-depth analysis of concurrent pattern detection showed a lack of research effort on the subject as previously noted by authors such as Hachicha and Ghorbel [13] and Du et al. [23]. The following research lines are suggested to extend the study and provide alternative solutions for the detection of simultaneous abnormal patterns.

The analysis of the concurrent pattern recognition approaches shows the need to compare studies assessing the performance of different approaches in terms of their requirements, effectiveness, and scenarios. The comparative analysis should include factors such as training time, amount of training data, knowledge of preprocessing techniques, and statistical measures such as ARL and ATTS. In addition, comparative studies between different machine learning techniques and statistical attributes are beneficial to determine the best alternative for pattern identification based on the conditions of each case of study. Likewise, the use of alternative machine learning instead of the widely applied ANN is recommended to explore potential improvements in classification performance. Several studies have demonstrated that SVMs have a better generalisation performance than ANN thanks to the principle of structural risk minimisation in which they are based. It is even possible to explore the possibility of working with deep learning techniques to handle high volumes of data.

The literature also indicated that the ICA technique is widely applied to separate the concurrent pattern into its corresponding single signals for most cases in which pattern decomposition is performed before the classification stage. Therefore, alternative techniques such as MRWA, SSA, PCA, and SOS should be encouraged to determine whether these methods have a positive impact on the quality of data fed to the classifier. The methods mentioned above may present limitations depending on the type of pattern to be evaluated. As a result, the proposal of a general methodology that includes all basic abnormal patterns and offers a good classification performance while maintaining simplicity is strongly recommended.

The taxonomic classification suggested the extraction of features to improve the quality of the data fed into the classifier by including potentially relevant information such as statistical and shape- or time-dependent characteristics. Extracting and selecting features is an important preprocessing step that has been shown to benefit the classification performance of machine learning algorithms [21,58,90]. Furthermore, determining an optimal feature subset can reduce the size of the input data and decompose complex functional relationships between many data and the associated production process [28]. In addition, most of the studies are focused on the combination of shift, trend, and cycle patterns, although there are 22 different types of concurrent patterns. Furthermore, most studies do not consider the identification of the change point, which can be of importance in the effective detection of the abnormal patterns and subsequent identification of assignable causes. Future research should consider more than two patterns at the same time, which is common in processes where several variables are monitored simultaneously.

The literature exposed an evident lack of studies that consider the existence of concurrent patterns when process assumptions are not those of a normally distributed and/or independent process. The occurrence of simultaneous abnormal patterns often arises in circumstances in which the process contains auto-correlated or non-normally distributed data. The design of new methodologies specifically targeted towards such process conditions would certainly be of great assistance in the effective detection of concurrent patterns in many industrial processes in which a normally distributed data assumption is not sustainable [21,38]. Moreover, automated processes have high levels of correlation, which makes it difficult to apply the methods developed to date in Industry 4.0 [91]. Additionally, studies trained and tested models using real and balanced data instead of simulated or unbalanced data because of the lack of public databases of real processes, considering different types of concurrent patterns. Therefore, proposals are still an approximation to real case studies, which makes their application difficult.

Regarding the evaluation of the proposed methods, the results showed that most of the studies applied an offline evaluation approach instead of an online one. This issue is relevant for pattern identification because it affects the detection speed and applicability in real systems. This means that most of the methodologies are trained in a static mode when the reality of systems is dynamic. Future research should consider an online approach to be aligned with the nature of the systems. Moreover, most of the studies did not analyse the impact of the window size in the model's performance.

Finally, there is a gap in the research related to performance indicators. Most of the analysed studies used detection accuracy metrics instead of an integration of the three types of performance indicators. Future studies should seek a balance between the three metrics to allow statistical and economic efficiency in the application of the methodologies to be proposed. This includes false alarms and their impact on the operation of the systems.

Author Contributions: Conceptualization, R.P.-N.; data curation, E.G.; formal analysis, E.G.; investigation, E.G. and A.P.-T.; methodology, E.G., R.P.-N. and M.J.-D.; project administration, R.P.-N.; supervision, R.P.-N.; writing—original draft, E.G., R.P.-N. and M.J.-D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The study did not report any data.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

α	Type I error
β	Type II error
ABPRL	Average both patterns run length ANN
ANN	Artificial neural networks
ARL	Average run length
ARL_0	In-control average run length
ARLIDX	Average run length index
ATPRL	Average target pattern run length
ATTS	Average time to signal
CA	Classification accuracy
CIC	Percentage of correctly identified concurrent CCPs
CP	Concurrent pattern
CCP	Control chart pattern
CLR	Classification rate
CR	Correct recognition
DNN	Deep neural networks
DT	Decision tree
ELM	Extreme learning machine
EPC	Engineering process control
EPCV	Engineering process control variables
ESMD	Extreme-point symmetric mode
ESV	Extreme-point symmetric variables
F1	F1-score
FA	False alarm
FCC	Fitted cosine curve
FFR	Fusion feature reduction variables
FLA	Fitted line analysis
IC	Independent components
ICA	Independent component analysis
MARS	Multivariate adaptive regression splines
MRWA	Multi-resolution wavelet analysis
PC	Principal component
PCA	Principal component analysis
PR	Precision
RA	Recognition accuracy
RE	Recall
RF	Random forest
RSA	Resampling
RS	Rough set
S1	Statistical features
S2	Shape features
S/ST/CO	Scaling/standardisation/codification
SCC	Statistical correlation coefficient
SDA	Sub-dictionary atoms
SO-BSS	Second-order blind source separation techniques
SOM	Second-order matrix
SP	Simple pattern
SPA	Spectral-based processing approach
SPC	Statistical Process Control
SRC	Sparse representation-based classification
SRSS	Sparse representation-based source separation
SSA	Singular spectrum analysis
SSAC	SSA components
SVM	Support vector machine

References

1. Shewhart, W.A. *Economic Control of Quality of Manufactured Product*; Macmillan and Co., Ltd.: London, UK, 1931.
2. Wang, J.; Kochhar, A.; Hannam, R. Pattern recognition for statistical process control charts. *Int. J. Adv. Manuf. Technol.* **1998**, *14*, 99–109. [CrossRef]
3. Pelegrina, G.D.; Duarte, L.T.; Jutten, C. Blind source separation and feature extraction in concurrent control charts pattern recognition: Novel analyses and a comparison of different methods. *Comput. Ind. Eng.* **2016**, *92*, 105–114. [CrossRef]
4. Shang, C.; You, F. Data analytics and machine learning for smart process manufacturing: Recent advances and perspectives in the big data era. *Engineering* **2019**, *5*, 1010–1016. [CrossRef]
5. Xu, J.; Lv, H.; Zhuang, Z.; Lu, Z.; Zou, D.; Qin, W. Control Chart Pattern Recognition Method Based on Improved One-dimensional Convolutional Neural Network. *IFAC-PapersOnLine* **2019**, *52*, 1537–1542. [CrossRef]
6. Zhang, M.; Zhang, X.; Wang, H.; Xiong, G.; Cheng, W. Features Fusion Exaction and KELM With Modified Grey Wolf Optimizer for Mixture Control Chart Patterns Recognition. *IEEE Access* **2020**, *8*, 42469–42480. [CrossRef]
7. Chiu, J.E.; Tsai, C.H. On-line concurrent control chart pattern recognition using singular spectrum analysis and random forest. *Comput. Ind. Eng.* **2021**, *159*, 107538. [CrossRef]
8. Maged, A.; Xie, M. Recognition of abnormal patterns in industrial processes with variable window size via convolutional neural networks and AdaBoost. *J. Intell. Manuf.* **2022**, 1–23. [CrossRef]
9. Paolanti, M.; Frontoni, E. Multidisciplinary pattern recognition applications: A review. *Comput. Sci. Rev.* **2020**, *37*, 100276. [CrossRef]
10. Xie, L.; Gu, N.; Li, D.; Cao, Z.; Tan, M.; Nahavandi, S. Concurrent control chart patterns recognition with singular spectrum analysis and support vector machine. *Comput. Ind. Eng.* **2013**, *64*, 280–289. [CrossRef]
11. Shao, Y.E.; Chang, P.Y.; Lu, C.J. Applying two-stage neural network based classifiers to the identification of mixture control chart patterns for an SPC-EPC process. *Complexity* **2017**, *2017*, 2323082. [CrossRef]
12. Lesany, S.; Ghomi, S.F.; Koochakzadeh, A. Development of fitted line and fitted cosine curve for recognition and analysis of unnatural patterns in process control charts. *Pattern Anal. Appl.* **2019**, *22*, 747–765. [CrossRef]
13. Hachicha, W.; Ghorbel, A. A survey of control-chart pattern-recognition literature (1991–2010) based on a new conceptual classification scheme. *Comput. Ind. Eng.* **2012**, *63*, 204–222. [CrossRef]
14. Guh, R.S.; Tannock, J. Recognition of control chart concurrent patterns using a neural network approach. *Int. J. Prod. Res.* **1999**, *37*, 1743–1765. [CrossRef]
15. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Int. J. Surg.* **2021**, *88*, 105906. [CrossRef] [PubMed]
16. Company, W.E. *Statistical Quality Control Handbook*; Western Electric: Rossville, GA, USA, 1958.
17. Pritchard, A. Statistical bibliography or bibliometrics. *J. Doc.* **1969**, *25*, 348–349.
18. Tandon, A.; Kaur, P.; Mäntymäki, M.; Dhir, A. Blockchain applications in management: A bibliometric analysis and literature review. *Technol. Forecast. Soc. Chang.* **2021**, *166*, 120649. [CrossRef]
19. Guh, R.S.; Hsieh, Y.C. A neural network based model for abnormal pattern recognition of control charts. *Comput. Ind. Eng.* **1999**, *36*, 97–108. [CrossRef]
20. Guh, R.S.; Tannock, J. A neural network approach to characterize pattern parameters in process control charts. *J. Intell. Manuf.* **1999**, *10*, 449–462. [CrossRef]
21. Chen, Z.; Lu, S.; Lam, S. A hybrid system for SPC concurrent pattern recognition. *Adv. Eng. Inform.* **2007**, *21*, 303–310. [CrossRef]
22. Lu, C.J.; Shao, Y.E.; Li, P.H. Mixture control chart patterns recognition using independent component analysis and support vector machine. *Neurocomputing* **2011**, *74*, 1908–1914. [CrossRef]
23. Du, S.; Huang, D.; Lv, J. Recognition of concurrent control chart patterns using wavelet transform decomposition and multiclass support vector machines. *Comput. Ind. Eng.* **2013**, *66*, 683–695. [CrossRef]
24. Al-Assaf, Y. Multi-resolution wavelets analysis approach for the recognition of concurrent control chart patterns. *Qual. Eng.* **2004**, *17*, 11–21. [CrossRef]
25. Yang, J.H.; Yang, M.S. A control chart pattern recognition system using a statistical correlation coefficient method. *Comput. Ind. Eng.* **2005**, *48*, 205–221. [CrossRef]
26. Wang, X. Hybrid abnormal patterns recognition of control chart using support vector machining. In Proceedings of the 2008 International Conference on Computational Intelligence and Security, Washington, DC, USA, 13–17 December 2008; IEEE: Piscataway, NJ, USA, 2008; Volume 2, pp. 238–241.
27. Jiang, P.; Liu, D.; Zeng, Z. Recognizing control chart patterns with neural network and numerical fitting. *J. Intell. Manuf.* **2009**, *20*, 625. [CrossRef]
28. Wang, C.H.; Dong, T.P.; Kuo, W. A hybrid approach for identification of concurrent control chart patterns. *J. Intell. Manuf.* **2009**, *20*, 409–419. [CrossRef]
29. Guh, R.S. Simultaneous process mean and variance monitoring using artificial neural networks. *Comput. Ind. Eng.* **2010**, *58*, 739–753. [CrossRef]
30. Lu, C.J.; Shao, Y.E.; Li, P.H.; Wang, Y.C. Recognizing mixture control chart patterns with independent component analysis and support vector machine. In *Advances in Neural Networks—ISNN 2010, Proceedings of the 7th International Symposium on Neural Networks, Shanghai, China, 6–9 June 2010*; Springer: Berlin/Heidelberg, Germany, 2010; pp. 426–431.

31. Ghomi, S.F.; Lesany, S.; Koochakzadeh, A. Recognition of unnatural patterns in process control charts through combining two types of neural networks. *Appl. Soft Comput.* **2011**, *11*, 5444–5456. [CrossRef]
32. Lu, C.J.; Shao, Y.E.; Chang, C.L. Applying ica and svm to mixture control chart patterns recognition in a process. In *Advances in Neural Networks—ISNN 2011, Proceedings of the 8th International Symposium on Neural Networks, Guilin, China, 29 May–1 June 2011*; Springer: Berlin/Heidelberg, Germany, 2011; pp. 278–287.
33. Shao, Y.E.; Lin, Y.; Chan, Y.C. Integrated use of ICA and ANN to recognize the mixture control chart patterns in a process. In *Advances in Data Mining. Applications and Theoretical Aspects, Proceedings of the 11th Industrial Conference on Data Mining, New York, NY, USA, 30 August–3 September 2011*; Springer: Berlin/Heidelberg, Germany, 2011; pp. 218–227.
34. Gu, N.; Cao, Z.; Xie, L.; Creighton, D.; Tan, M.; Nahavandi, S. Identification of concurrent control chart patterns with singular spectrum analysis and learning vector quantization. *J. Intell. Manuf.* **2013**, *24*, 1241–1252. [CrossRef]
35. Lesany, S.; Koochakzadeh, A.; Fatemi Ghomi, S. Recognition and classification of single and concurrent unnatural patterns in control charts via neural networks and fitted line of samples. *Int. J. Prod. Res.* **2014**, *52*, 1771–1786. [CrossRef]
36. Lu, C.J.; Shao, Y.E.; Li, C.C. Recognition of concurrent control chart patterns by integrating ICA and SVM. *Appl. Math. Inf. Sci.* **2014**, *8*, 681–689. [CrossRef]
37. Chompu-inwai, R.; Thaiupathump, T. Improved ICA-based mixture control chart patterns recognition using shape related features. In Proceedings of the 2015 IEEE Conference on Control Applications (CCA), Sydney, Australia, 21–23 September 2015; IEEE: Piscataway, NJ, USA; pp. 484–489.
38. Thaiupathump, T.; Chompu-Inwai, R. Impact of kurtosis on performance of mixture control chart patterns recognition using Independent Component Analysis and neural networks. In Proceedings of the 2015 4th International Conference on Advanced Logistics and Transport (ICALT), Valenciennes, France, 20–22 May 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 94–99.
39. Yang, W.A.; Zhou, W.; Liao, W.; Guo, Y. Identification and quantification of concurrent control chart patterns using extreme-point symmetric mode decomposition and extreme learning machines. *Neurocomputing* **2015**, *147*, 260–270. [CrossRef]
40. Zhang, M.; Cheng, W. Recognition of mixture control chart pattern using multiclass support vector machine and genetic algorithm based on statistical and shape features. *Math. Probl. Eng.* **2015**, *2015*, 382395. [CrossRef]
41. Zhang, M.; Cheng, W.; Guo, P. Intelligent recognition of mixture control chart pattern based on quadratic feature extraction and SVM with AMPSO. *J. Coast. Res.* **2015**, *73*, 304–309. [CrossRef]
42. Mozafari, A.S.; Aminnayeri, M. Concurrent Control Chart Pattern Recognition Using a Novel Source Separation Method based on Sparse Representation. In Proceedings of the 46th International Conference on Computers & Industrial Engineering 2016 (CIE46), Tianjin, China, 29–31 October 2016.
43. Shao, Y.E.; Chiu, C.C. Applying emerging soft computing approaches to control chart pattern recognition for an SPC–EPC process. *Neurocomputing* **2016**, *201*, 19–28. [CrossRef]
44. Hong, Z.; Li, Y.; Zeng, Z. Convolutional neural network for control chart patterns recognition. In Proceedings of the 3rd International Conference on Computer Science and Application Engineering, Sanya, China, 22–24 October 2019; pp. 1–9.
45. Miao, Z.; Yang, M. Control chart pattern recognition based on convolution neural network. In *Smart Innovations in Communication and Computational Sciences*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 97–104.
46. Kadakadiyavar, S.; Ramrao, N.; Singh, M.K. Efficient mixture control chart pattern recognition using adaptive RBF neural network. *Int. J. Inf. Technol.* **2020**, *12*, 1271–1280. [CrossRef]
47. Kao, L.J.; Chiu, C.C. Application of integrated recurrent neural network with multivariate adaptive regression splines on SPC-EPC process. *J. Manuf. Syst.* **2020**, *57*, 109–118. [CrossRef]
48. Shao, Y.E.; Hu, Y.T. Using machine learning classifiers to recognize the mixture control chart patterns for a multiple-input multiple-output process. *Mathematics* **2020**, *8*, 102. [CrossRef]
49. Zhang, M.; Yuan, Y.; Wang, R.; Cheng, W. Recognition of mixture control chart patterns based on fusion feature reduction and fireworks algorithm-optimized MSVM. *Pattern Anal. Appl.* **2020**, *23*, 15–26. [CrossRef]
50. Yu, Y.; Zhang, M. Control chart recognition based on the parallel model of CNN and LSTM with GA optimization. *Expert Syst. Appl.* **2021**, *185*, 115689. [CrossRef]
51. Cheng, C.S.; Chen, P.W.; Ho, Y. Control Chart Concurrent Pattern Classification Using Multi-Label Convolutional Neural Networks. *Appl. Sci.* **2022**, *12*, 787. [CrossRef]
52. Chang, C.C.; Lin, C.J. LIBSVM: A library for support vector machines. *ACM Trans. Intell. Syst. Technol. (TIST)* **2011**, *2*, 1–27. [CrossRef]
53. Torng, C.C.; Hwang, C.H. Recognition of Concurrent Control Chart Patterns in Autocorrelated Processes Using Support Vector Machine. *Proc. Eng. Technol. Innov.* **2016**, *3*, 22–24.
54. Huberts, L.C.; Schoonhoven, M.; Goedhart, R.; Diko, M.D.; Does, R.J. The performance of control charts for large non-normally distributed datasets. *Qual. Reliab. Eng. Int.* **2018**, *34*, 979–996. [CrossRef]
55. Psarakis, S.; Papaleonida, G. SPC procedures for monitoring autocorrelated processes. *Qual. Technol. Quant. Manag.* **2007**, *4*, 501–540. [CrossRef]
56. Chen, S.; Yu, J. Deep recurrent neural network-based residual control chart for autocorrelated processes. *Qual. Reliab. Eng. Int.* **2019**, *35*, 2687–2708. [CrossRef]
57. Ranaee, V.; Ebrahimzadeh, A. Control chart pattern recognition using a novel hybrid intelligent method. *Appl. Soft Comput.* **2011**, *11*, 2676–2686. [CrossRef]

58. Cheng, H.P.; Cheng, C.S. Control chart pattern recognition using wavelet analysis and neural networks. *J. Qual.* **2009**, *16*, 311–321.
59. Guh, R.S. Integrating artificial intelligence into on-line statistical process control. *Qual. Reliab. Eng. Int.* **2003**, *19*, 1–20. [CrossRef]
60. Du, S.; Lv, J.; Xi, L. An integrated system for on-line intelligent monitoring and identifying process variability and its application. *Int. J. Comput. Integr. Manuf.* **2010**, *23*, 529–542. [CrossRef]
61. Asadi, A.; Farjami, Y. Online mean shift detection in multivariate quality control using boosted decision tree learning. *J. Syst. Manag.* **2019**, *5*, 81–106.
62. Lu, Z.; Wang, M.; Dai, W. A condition monitoring approach for machining process based on control chart pattern recognition with dynamically-sized observation windows. *Comput. Ind. Eng.* **2020**, *142*, 106360. [CrossRef]
63. Albers, W.; Kallenberg, W.C. Empirical non-parametric control charts: Estimation effects and corrections. *J. Appl. Stat.* **2004**, *31*, 345–360. [CrossRef]
64. Yu, J. Gaussian mixture models-based control chart pattern recognition. *Int. J. Prod. Res.* **2012**, *50*, 6746–6762. [CrossRef]
65. Fuqua, D.; Razzaghi, T. A cost-sensitive convolution neural network learning for control chart pattern recognition. *Expert Syst. Appl.* **2020**, *150*, 113275. [CrossRef]
66. Ramaker, H.J.; van Sprang, E.N.; Westerhuis, J.A.; Smilde, A.K. The effect of the size of the training set and number of principal components on the false alarm rate in statistical process monitoring. *Chemom. Intell. Lab. Syst.* **2004**, *73*, 181–187. [CrossRef]
67. Kang, J.H.; Kim, S.B. False alarm classification for multivariate manufacturing processes of thin film transistor–liquid crystal displays. *J. Process Control* **2015**, *35*, 21–29. [CrossRef]
68. Sohaimi, N.A.M.; Masood, I.; Nor, D.M. Bivariate SPC Chart Pattern Recognition Using Modular-Neural Network. *J. Phys. Conf. Ser.* **2018**, *1049*, 012096.
69. Wuest, T.; Weimer, D.; Irgens, C.; Thoben, K.D. Machine learning in manufacturing: Advantages, challenges, and applications. *Prod. Manuf. Res.* **2016**, *4*, 23–45. [CrossRef]
70. Guh, R.S.; Zorriassatine, F.; Tannock, J.; O'Brien, C. On-line control chart pattern detection and discrimination—A neural network approach. *Artif. Intell. Eng.* **1999**, *13*, 413–425. [CrossRef]
71. Gauri, S.K.; Chakraborty, S. A study on the various features for effective control chart pattern recognition. *Int. J. Adv. Manuf. Technol.* **2007**, *34*, 385–398. [CrossRef]
72. Cheng, Z.; Ma, Y. A research about pattern recognition of control chart using probability neural network. In Proceedings of the 2008 ISECS International Colloquium on Computing, Communication, Control, and Management, Guangzhou, China, 3–4 August 2008; IEEE: Piscataway, NJ, USA, 2008; Volume 2, pp. 140–145.
73. Awadalla, M.H.; Sadek, M.A. Spiking neural network-based control chart pattern recognition. *Alex. Eng. J.* **2012**, *51*, 27–35. [CrossRef]
74. Cheng, C.S.; Ho, Y.; Chiu, T.C. End-to-end control chart pattern classification using a 1D convolutional neural network and transfer learning. *Processes* **2021**, *9*, 1484. [CrossRef]
75. Zan, T.; Su, Z.; Liu, Z.; Chen, D.; Wang, M.; Gao, X. Pattern Recognition of Different Window Size Control Charts Based on Convolutional Neural Network and Information Fusion. *Symmetry* **2020**, *12*, 1472. [CrossRef]
76. Khan, S.H.; Hayat, M.; Bennamoun, M.; Sohel, F.A.; Togneri, R. Cost-sensitive learning of deep feature representations from imbalanced data. *IEEE Trans. Neural Netw. Learn. Syst.* **2017**, *29*, 3573–3587. [PubMed]
77. Ünlü, R. Cost-oriented LSTM methods for possible expansion of control charting signals. *Comput. Ind. Eng.* **2021**, *154*, 107163. [CrossRef]
78. Xanthopoulos, P.; Razzaghi, T. A weighted support vector machine method for control chart pattern recognition. *Comput. Ind. Eng.* **2014**, *70*, 134–149. [CrossRef]
79. Apsemidis, A.; Psarakis, S.; Moguerza, J.M. A review of machine learning kernel methods in statistical process monitoring. *Comput. Ind. Eng.* **2020**, *142*, 106376. [CrossRef]
80. Xin-chun, C.; Peng, D.; Nai-qing, Y.; Meng-xue, B. Study on discrete manufacturing quality control technology based on big data and pattern recognition. *Math. Probl. Eng.* **2021**, *2021*, 8847094. [CrossRef]
81. Tran, P.H.; Ahmadi Nadi, A.; Nguyen, T.H.; Tran, K.D.; Tran, K.P. Application of Machine Learning in Statistical Process Control Charts: A Survey and Perspective. In *Control Charts and Machine Learning for Anomaly Detection in Manufacturing*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 7–42.
82. Zan, T.; Liu, Z.; Su, Z.; Wang, M.; Gao, X.; Chen, D. Statistical process control with intelligence based on the deep learning model. *Appl. Sci.* **2020**, *10*, 308. [CrossRef]
83. Viharos, Z.J.; Jakab, R. Reinforcement Learning for Statistical Process Control in Manufacturing. *Measurement* **2021**, *182*, 109616. [CrossRef]
84. Chen, X.W.; Lin, X. Big data deep learning: Challenges and perspectives. *IEEE Access* **2014**, *2*, 514–525. [CrossRef]
85. Haghtalab, S.; Xanthopoulos, P.; Madani, K. A robust unsupervised consensus control chart pattern recognition framework. *Expert Syst. Appl.* **2015**, *42*, 6767–6776. [CrossRef]
86. Khormali, A.; Addeh, J. A novel approach for recognition of control chart patterns: Type-2 fuzzy clustering optimized support vector machine. *ISA Trans.* **2016**, *63*, 256–264. [CrossRef] [PubMed]
87. Zaman, M.; Hassan, A. Improved statistical features-based control chart patterns recognition using ANFIS with fuzzy clustering. *Neural Comput. Appl.* **2019**, *31*, 5935–5949. [CrossRef]

88. Golilarz, N.A.; Addeh, A.; Gao, H.; Ali, L.; Roshandeh, A.M.; Munir, H.M.; Khan, R.U. A new automatic method for control chart patterns recognition based on ConvNet and harris hawks meta heuristic optimization algorithm. *IEEE Access* **2019**, *7*, 149398–149405. [CrossRef]
89. De la Torre Gutierrez, H.; Pham, D. Estimation and generation of training patterns for control chart pattern recognition. *Comput. Ind. Eng.* **2016**, *95*, 72–82. [CrossRef]
90. Hassan, A.; Baksh, M.S.N.; Shaharoun, A.M.; Jamaluddin, H. Improved SPC chart pattern recognition using statistical features. *Int. J. Prod. Res.* **2003**, *41*, 1587–1603. [CrossRef]
91. Quintero-Arteaga, C.; Peñabaena-Niebles, R.; Vélez, J.I.; Jubiz-Diaz, M. Statistical design of an adaptive synthetic X control chart for autocorrelated processes. *Qual. Reliab. Eng. Int.* **2022**, *2022*, 9629170. [CrossRef]