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Analysis and Perspectives on Multivariate Statistical Process Control Charts used in the Industrial Sector: a Systematic Literature Review

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Abstract
The objective of this article is to carry out a systematic review of the literature on multivariate statistical process control (MSPC) charts used in industrial processes. The systematic review was based on articles published via Web of Science and Scopus in the last 10 years, from 2010 to 2020, with 51 articles on the theme identified. This article sought to identify in which industry the MSPC charts are most applied, the types of multivariate control charts used and probability distributions adopted, as well as pointing out the gaps and future directions of research. The most commonly represented industry was electronics, featuring in approximately 25% of the articles. The MSPC chart most frequently applied in the industrial sector was the traditional T^2 of Harold Hotelling (Hotelling, 1947), found in 26.56% of the articles. Almost half of the combinations between the probabilistic distribution and the multivariate control graphs, i.e., 49.4%, considered that the data followed a normal distribution. Gaps and future directions for research on the topic are presented at the end.

Keywords
Multivariate statistical process control, Systematic review, Control chart, Manufacturing, Industrial.

Introduction

Due to the modernization process of industrial manufacturing, there are situations in which simultaneous monitoring of quality characteristics is necessary and independent control of variables can lead to wrong decisions (Maboudou-Tchao et al., 2018). MSPC charts help to understand the correlation and dependence between the variables (Pan & Lee, 2010). Several multivariate control chart types are found in the literature, such as Hotelling's T^2 (Galaverna et al., 2018; Darmanto & Astutik, 2017), multivariate exponentially weighted moving average (MEWMA) (Haq et al., 2018; Abreu & Schaffer, 2017) and multivariate cumulative sum (MCUSUM) (Nidsunkid et al., 2018; Sukparungsee et al., 2017).

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Wade and Woodall (1993) discussed the concept of cause-selecting control charts. Lowry and Montgomery (1997) published a review of studies on multivariate quality control charts published since 1980, where the main charts discussed were CUSUM and EWMA. Bersimis, Psarakis and Panaretos (2007) discussed procedures for the implementation of MSPC control charts. Prajapati and Mahapatra (2009) provided a summary of the control charts used to monitor the process mean and dispersion, comprising publications from 1931 to 2008. Topalidou and Psarakis (2009) reviewed the studies on multinomial and multiattribute quality control charts and the main tools used. None of these articles undertook a systematic literature review and all were published before the period of analysis considered in the present paper. We found no similar studies on the subject in our search process.

The focus of this review is to analyze a group of papers that used MSPC charts in industrial processes. It is not the purpose of this analysis to review all articles on the subject, therefore, the research was restricted to publications from the last 10 years, between 2010 and 2020. The reason for choosing this period was to check the emerging MSPC charts applied in manufacturing processes, since there is an accelerated modernization of this area, including the process control mechanisms. We tried to answer the following questions:

- What is the type of industry where multivariate control charts were most applied?
- Which multivariate control chart was most frequently applied in the industrial sector?
- Which type of time series distribution was most used in multivariate control charts in the industrial sector?
- What are the gaps and future directions for research on the theme?

The most appropriate method to answer these questions is a systematic literature review (SLR), because it helps to understand the existing knowledge about a topic and reduces possible bias. The methodology was based on the protocol systematized by Biolchini et al. (2007), Kitchenham (2004) and Tranfield, Denyer and Smart (2003).

Research methodology

The review protocol by Tranfield, Denyer and Smart (2003) was followed, together with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009) to select only articles on the theme and ensure methodological rigor necessary for an SLR.

The articles were selected from the Web of Science and Scopus databases, as well as in the work of Varela et al. (2018) and Gladysz and Buczacki (2018). The search was conducted on March 30th 2020. Keywords used in the search were combined with the Boolean operators 'OR' and 'AND' (Table 1). We considered only full articles published in English, without restricting the publication period.

The sequencing, exclusion criteria and quantity of articles found in each stage are shown in Fig. 1.

Based on the inclusion/exclusion criteria, 51 articles were identified as adequate for the SLR. All ar-

Table 1
Search strings

Base	Search string	Number of articles
Web of Science	TS = ((manufactur* OR producti*) AND ("Multivariate Control Chart*" OR ("SPC Chart*" AND multivariate) OR "multivariate statistical process control chart*" OR "MSPC chart*"))	131
Scopus	TITLE-ABS-KEY-AUTH((manufactur* OR producti*) AND ("Multivariate Control Chart*" OR ("SPC Chart*" AND multivariate) OR "multivariate statistical process control chart*" OR "MSPC chart*"))	117
	Total	248

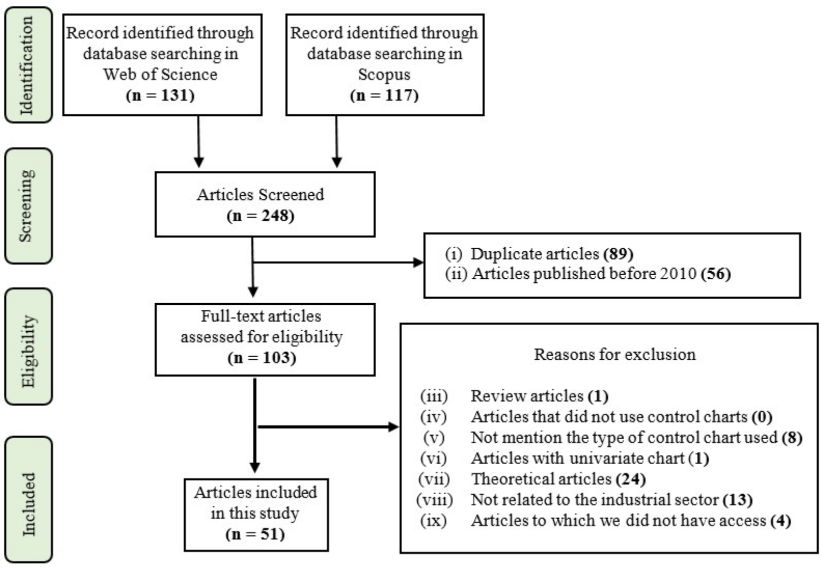

Fig. 1. Records identified, screened and included in systematic literature review.
Source: Based on the PRISMA flow diagram (Franceschini, Galetto & Genta, 2005)

ticles remaining after applying the exclusion criteria were read in full.

Study characteristics

The number of articles on the subject has increased in recent years. Table 2 provides the following information for each article in this review. Each article received an identification code (id #).

In the first period (2010–2015), 24 articles were published and in the second period (2016–2020), 27 articles. As the search was conducted in March 2020, the number of articles in the second five-year period may increase.

The country of origin of most authors was China, corresponding to approximately 25% of publications (13 articles) followed by South Korea and the USA (nine articles each), Italy (five articles), Taiwan (four articles), Brazil and Malaysia (three articles each).

Table 2
Information for each article: year of publication, authors, journal and authors' country of origin

		id#	Authors	Journal	Year	Country
Number of articles	2010–2015 = 24 articles	A1	Capizzi and Masarotto	Technometrics	2011	Italy
		A2	Triantafyllopoulos	Journal of Time Series Analysis	2011	England
		A3	Cheng and Cheng	Computers & Industrial Engineering	2011	Taiwan
		A4	Verdier and Ferreira	IEEE Transactions on Semiconductor Manufacturing	2011	France
		A5	Cheng, Ma and Bu	Communications in Statistics-Simulation and Computation	2011	China
		A6	Snoussi	Journal of Applied Statistics	2011	Tunisia
		A7	Xiong, Gong and Qu	Journal of Pharmaceutical and Biomedical Analysis	2012	China
		A8	Ávila et al.	Biotechnology Progress	2012	Brazil
		A9	Chang et al.	Quality Engineering	2012	USA and Taiwan
		A10	Del Val et al.	International Journal of Advanced Manufacturing Technology	2013	Spain and USA
		A11	Kang and Kim	International Journal of Production Research	2013	South Korea
		A12	Babamoradi, Berg and Rinnan	Chemometrics and Intelligent Laboratory Systems	2013	Denmark
		A13	Corain and Salmaso	Applied Stochastic Models in Business and Industry	2013	Italy
		A14	Zeng et al.	Journal of Pharmaceutical and Biomedical Analysis	2013	China
		A15	Li, Zhang and Jeske	Journal of Nonparametric Statistics	2013	USA
		A16	Li et al.	Mathematical Problems in Engineering	2013	China
		A17	He and Zhou	International Journal of Production Research	2014	USA and China
		A18	Yang and Zhou	Journal of Intelligent Manufacturing	2015	China
		A19	Kang and Kim	Journal of Process Control	2015	South Korea
		A20	Franceschini, Galetto and Genta	Precision Engineering	2015	Italy
		A21	Yang	Journal of Intelligent Manufacturing	2015	China
		A22	Ou, Chen and Khoo	International Journal of Production Research	2015	Singapore and Malaysia
		A23	Lee et al.	European Journal of Industrial Engineering	2015	South Korea
		A24	Yan, Paynabar and Shi	IEEE Transactions on Automation Science and Engineering	2015	USA

Table 2 [cont.]

		id#	Authors	Journal	Year	Country
Number of articles	2016–2020 = 27 articles	B25	Sales et al.	Computers & Chemical Engineering	2016	Brazil and Spain
		B26	Kan, Cheng and Yang	Journal of Manufacturing Systems	2016	USA
		B27	Harris et al.	Quality and Reliability Engineering International	2016	England
		B28	Kaewsuwan et al.	International Journal of Food Engineering	2016	Thailand and Taiwan
		B29	Chen and Liang	International Journal of Advanced Manufacturing Technology	2016	USA
		B30	Li et al.	Sensors and Actuators B-Chemical	2016	China
		B31	Zhang, Chen and Zou	Journal of Quality Technology	2016	Singapore and China
		B32	Marcondes Filho and Oliveira	International Journal of Advanced Manufacturing Technology	2016	Brazil
		B33	Cheng and Lee	Journal of the Chinese Institute of Engineers	2016	Taiwan
		B34	Kang, Yu and Kim	Journal of Process Control	2016	South Korea and USA
		B35	Choung, Kang and Kim	Journal of Process Control	2017	South Korea
		B36	Aslam et al.	Journal of Applied Statistics	2017	Saudi Arabia, Tanzania, Pakistan and South Korea
		B37	Xiang, Tsung and Pu	Technometrics	2017	China
		B38	Sohaimi et al.	Journal of Telecommunication, Electronic and Computer Engineering	2017	Malaysia
		B39	Xia et al.	Advances in Mechanical Engineering	2018	China and USA
		B40	Mostajeran, Iranpanah and Noorossana	Journal of Modern Applied Statistical Methods	2018	Iran
		B41	Lee and Kim	Engineering Applications of Artificial Intelligence	2018	South Korea
		B42	Haddad and Alsmadi	Punjab University Journal of Mathematics	2018	Saudi Arabia
		B43	Xia, Jian and Tao	Journal of Ambient Intelligence and Humanized Computing	2019	China
		B44	Grassi et al.	Foods	2019	Italy
		B45	Zhang, Liu and Jung	Journal of the Operational Research Society	2019	China and South Korea
		B46	Grasso and Colosimo	Robotics and Computer-Integrated Manufacturing	2019	Italy
		B47	Sangahn	Journal of Systems Engineering and Electronics	2019	USA
		B48	Chong et al.	Quality and Reliability Engineering International	2019	Malaysia, Pakistan and France
		B49	Guerrero, Pombo and Costa	Journal of Industrial Engineering International	2019	Colombia
		B50	Haanchumpol, Sudasna-na-Ayudthyan and Singhtaun	Engineering Science and Technology, an International Journal	2019	Thailand
		B51	Liu, Liu and Jung	Quality Technology and Quantitative Management	2020	China and South Korea

Results and discussion

Article classification by industry type

Table 3 contains the article classification based on industry type.

Table 3
Classification based on industry type

Industry	Number of articles	Authors
Electronic	13 (25.5%)	[A1, A4, A11, A13, A19, A20, A23, B31, B34, B35, B37, B41, B50]
Health	6 (11.8%)	[A7, A14, B30, B46, B47, B48]
Metallurgical	5 (10.0%)	[A10, A17, A24, B26, B27]
Food	4 (8.0%)	[A22, B28, B40, B44]
Energy	2 (4.0%)	[A8, B25]
Textile	1 (2.0%)	[A12]
Agricultural	1 (2.0%)	[B49]
Chemical	1 (2.0%)	[A18]
Construction	1 (2.0%)	[A9]
Undefined	3 (5.7%)	[A2, A5, A21]
Simulated data	14 (27.5%)	[A3, A6, A15, A16, B29, B32, B33, B36, B38, B39, B42, B43, B45, B51]

The industry most represented in the articles was electronics (thirteen). In three articles, the application area was not explained, and were classified as 'undefined'. Fourteen articles used simulated data in their work. A statistical control chart can relate to the product or process. Figure 2 shows a longitudinal classification with a product or process emphasis.

Approximately 49% of the empirical studies applied MSPC charts in processes, 35% in the product and, 16% were undefined. The number of publications in the area of health has grown, especially demonstrating statistical control of the process. In the metallurgical, electronics, construction and energy industries, studies mainly emphasized processes. All publications in the food, agricultural and chemical industry aimed to apply MSPC charts to monitor characteristics related to product quality.

Multivariate control charts used

We identified 24 MSPC chart types in the 51 selected articles. Table 4 shows the MSPC charts used in these articles, the industrial sector analyzed and the year of publication.

Traditional charts were the most used: Hotelling's T^2 – 17 articles. Twelve articles used more than one MSPC chart. The purposes of using more than one MSPC chart type were (i) combination of control charts and (ii) comparison of traditional charts with the proposed MSPC chart.

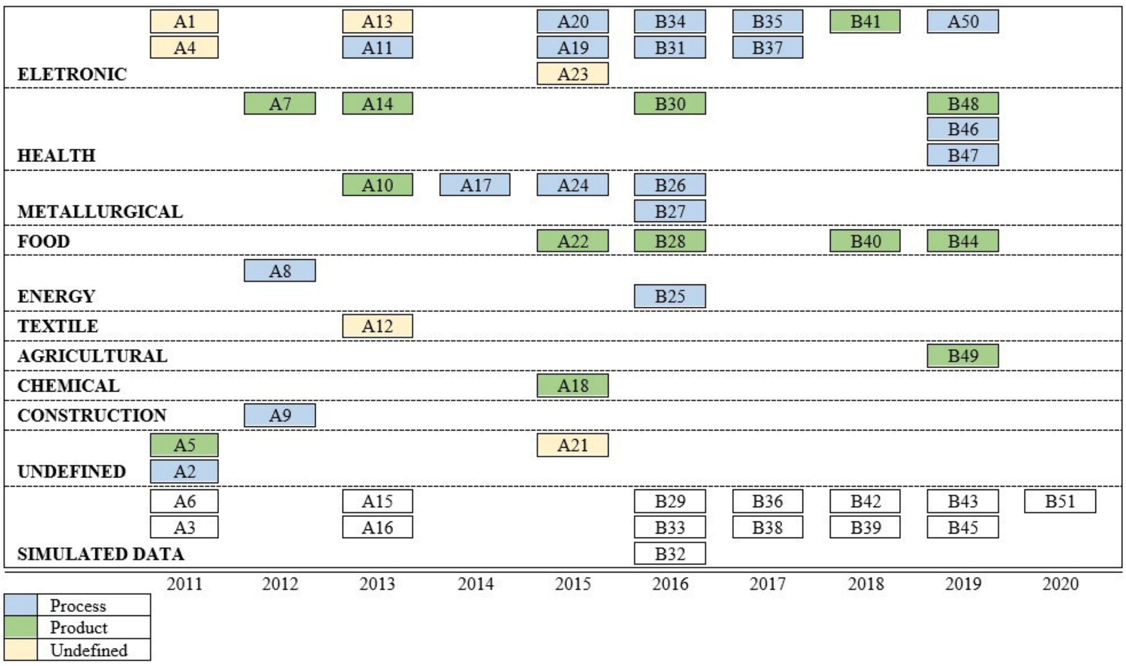

Fig. 2. Records identified, screened and included in systematic literature review.
Source: Based on the PRISMA flow diagram (Franceschini, Galetto and Genta, 2005)

Table 4
Longitudinal classification with a product or process emphasis

MSPC Chart	Year											Number of papers (%)
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	
T^2 de Hotelling chart						A19	B25					17(26.56%)
				A12		A20	B26					
			A7	A14		A23	B28		B40	B44		
			A9	A16		A24	B30		B42	B48		
lSl chart		A3										6 (9.38%)
		A5		A10		A20	B33			B49		
MEWMA control chart		A1								B47		6 (9.38%)
		A2				A21		B37		B50		
MCUSUM control chart				A15		A21		B37	B39	B43		5 (7.82%)
SPE chart			A8	A12		A24				B44		4 (6.25%)
Cluster-based approach		A4		A11			B34					3 (4.69%)
DModX			A7	A14			B30					3 (4.69%)
SVDD – based control charts									B41	B43		2 (3.13%)
CCPR						A18		B38				2 (3.13%)
NPC chart				A13			B27					2 (3.13%)
VAR residual chart		A6										1 (1.56%)
DNW control charts											B51	1 (1.56%)
FL-VS chart										B45		1 (1.56%)
K chart										B46		1 (1.56%)
DLPP chart					A17							1 (1.56%)
MQE-SOM								B35				1 (1.56%)
MPD chart								B36				1 (1.56%)
MSPRT						A22						1 (1.56%)
Scores chart			A7									1 (1.56%)
FLSPC System							B29					1 (1.56%)
DFM-GoF							B31					1 (1.56%)
COt							B32					1 (1.56%)
Biplot			A9									1 (1.56%)
SCC V chart		A6										1 (1.56%)

Notes: Each number in the figure corresponds to a sample article, according to the identification code (id#) listed in Table 2

	Electronic		Textile
	Helth		Agriculture
	Metallurgical		Chemical
	Food		Construction
	Energy		Simulated data and undefined

Control charts based on cluster analysis were exclusively applied in the electronics sector and the distance to the model X (DModX) control chart in the health area. Hotelling's T^2 chart proved to be very versatile, being applied in several industries.

Probability distribution in MSPC

Table 5 shows the distributions, types of industries and MSPC used in the articles.

Table 5
Distributions, types of industries and MSPC used

MSPC chart	Distribution																
	Normal	T	Gamma	Banana-Shaped	Chi square	F	Non normal	Log-normal	Beta	Poisson	Gaussian	Dirichlet	DModX	Cauchy	Wishart	Non param-etric	Not unquoted
T^2 de Hotelling chart	A7	A19	A19	A19	B48	A12	A23				B42	B26	B25				A9
	A16	B25	B40			A14											B44
	A19	B40															
	A20																
	A24																
	B28																
	B30																
	B40																
	B42																
	B48																
lSl chart	A3																
	A5																
	A10																
	A20																
	B33																
	B49																
MEWMA chart	A1		B50						B47						A2		
	A21																
	B37																
MCUSUM chart	A15	A15	A15		A15									A15			
	A21																
	B37																
	B39																
	B43																
SPE chart	A24				A8												B44
					A12												
Cluster-based	A11			A11												A4	
	B34			B34													
DModX	A7					A14											
	B30																
SVDD charts	B41	B41		B41				B41									
	B43																
CCPR							A18										B38
NPC chart	A13																
	B27																
VAR chart	A6																
DNW	B51																
FL-VS	B45																
K chart																	B46
DLPP	A17																
MQE	B35	B35	B35	B35				B35									
MPD chart										B36							
MSPRT	A22																
Scores	A7																
FLSPC																	B29
DFM-GoF	B31	B31	B31														
COt	B32																
Biplot																	A9
SCC V	A6																
Times the distribution appears	43	7	6	5	4	3	2	2	1	1	1	1	1	1	1	1	7
Percentage (%)	49.4	8.0	6.8	5.7	4.6	3.5	2.2	2.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	8.0

Notes: Each number in the figure corresponds to a sample article, according to the identification code (id#) listed in Table 2

Electronic	Energy	Construction
Helth	Textile	Simulated data and undefined
Metallurgical	Agriculture	
Food	Chemical	

Hotelling's T^2 chart was tested with a wide range of distributions. All studies that normalized the observations or indicated that the data followed a normal distribution variation, like skew-normal, normal non-homogeneous, heavy-tailed and skewed, were classified as normal distribution. Approximately half of the distribution and MSPC combinations considered that the data had a normal distribution (49.4%), followed by t distribution (8%), gamma (6.8%), banana-shaped (5.7%), chi-square (4.6%), F (3.5%), log-normal (2.2%) and non-normal (2.2%). The other distributions types were considered in only one MSPC and distribution type was not specified in 8% of combinations.

The applications considering banana-shaped distribution were all from the electronic sector. Some MSPCs assumed the ideal distribution for the approach type, for example, all studies using the |S|chart considered that the observations followed a normal distribution, one of the assumptions for the use of this MSPC. Other control charts were developed for application to data with a specific distribution, such as the MPD chart, recommended for observations that follow the Poisson distribution.

More than one distribution type was considered in 13 articles. Generally, these studies aimed to propose a new MSPC, where the suggested chart was tested with two or more distribution types. In other cases, the same distribution was used, but tested different MSPCs. The intention was to assess which was the best MSPC for a given distribution type.

Benefits, gaps and future directions

Table 6 shows the main benefits obtained from applying MSPC charts according to the authors of the selected articles.

More than half of the authors (56.4%) agreed that the main advantage of applying the MSPC is the fault detection optimization and the reduction of false alarms. In eight other articles, continuous learning was cited as an advantage, referring to the quick adjustment to time-varying conditions, providing online process monitoring.

The authors of some of the selected articles highlighted the gaps and future directions for research on the theme (Table 7).

Most authors suggested future MSPC combination studies or chart comparison. One difficulty found by using MSPC charts was the number of time series observations (n) and the number of model variables (p). They suggested a more comprehensive simulation involving a greater number of p-variables and n-observations. Other authors, pointed out the importance of continuing studies that seek to optimize identification product and process failures.

Other research gaps and future research directions were highlighted: integrate or replace variables used with others; extend the study to autocorrelated process; analyze the feasibility of the proposed method in technical or financial terms; implement algorithms based on missing value estimates; diagnose the causes of process abnormalities; apply the proposed MSPC

Table 6
Main results obtained from applying MSPC charts in industrial processes

Benefits	Number of articles	Authors, Date
Fault detection optimization and the reduction of false alarms	35 (56.4%)	[A1, A2, A3, A7, A10, A11, A12, A13, A16, A17, A18, A20, A21, A22, A23, A24, B26, B27, B32, B33, B34, B35, B36, B37, B38, B40, B41, B43, B44, B45, B46, B47, B48, B49, B50]
Continuous learning: quick adjustment to time-varying conditions	8 (12.9%)	[A5, A6, A19, B29, B31, B33, B34, B42]
Improving of product quality through defect reduction	4 (6.5%)	[A9, B25, B28, B43]
Identified the variables responsible for the process variation	4 (6.5%)	[A4, A15, B32, B44]
Robustness against incorrect model specifications, especially the distribution type	4 (6.5%)	[A14, B30, B34, B39]
Others	7 (11.2%)	[A1, A4, A7, A8, B25, B28, B43]

Table 7
Research gaps and future research directions

Research gaps	Number of articles	Authors, Date
MSPC combination studies or chart comparison	11 (28.9%)	[A10, A15, A18, A20, A21, A22, B32, B35, B38, B47, B48]
More comprehensive simulation: databases with more observations (n) or with a greater number of variables (p)	6 (15.8%)	[A1, A2, A20, A21, B49, B50]
Optimize identification product and process failures	5 (13.2%)	[A4, A13, B34, B36, B40]
Integrate or replace variables used with others	3 (7.9%)	[A8, B25, B27]
Extend the study to autocorrelated process	2 (5.3%)	[B30, B42]
Analyze the feasibility of the proposed method in technical or financial terms – cost due to fault identification error	2 (5.3%)	[A16, B45]
Implement algorithms based on missing value estimates	2 (5.3%)	[A11, A18]
Diagnose the causes of process abnormalities	2 (5.3%)	[A20, A29]
Others	5 (13.0%)	[A1, A18, B26, B33, B46]

in another sector; apply the MSPC to monitor a nonparametric process; enlarge for categorical response variables; process automation; and use other criteria to test chart performance. Some authors did not mention research gaps and future research directions.

Similar research results

Ueda et al. (2021) carried out a systematic literature review (SLR), however, focused only in researches developed in Brazil. Other SLR related to the theme do not focus on answering the questions raised in this article, such as the type of industry, MSPC most frequently applied in the industrial sector, time series type distribution, gaps and future directions for research. Rodrigues et al. (2021), Peres and Fogliatto (2018) presented systematic literature reviews to assist the selection of variables in MSPC. In other studies, SLR performance was focused on a specific sector (Lim & Antony, 2018).

On the other hand, You-Jin, Fan and Chia-Yu (2020) investigated through SLR the consequences of failure detection in industrial manufacturing processes, pointing out the benefits of quick diagnosis. Subbulakshmi et al. (2017) reinforce through a SLR the essential role of statistical process control.

Therefore, the authors did not find similar studies, that is, a systematic literature review (SLR) on multivariate statistical process control (MSPC) charts used in industrial processes.

Guidelines and suggestions for future research: perspectives

According to Kurnia and Hamsal (2021), a SLR consists of a rigorous methodology for evaluating the literature on a topic of interest. Therefore, the guidelines and suggestions for future research are given in accordance with the results found in the present SLR.

In terms of application and development of control charts, the authors suggest combining and comparing performance between MSPC charts. In addition, MSPC charts should be developed focused on the number of time series observations (n) and on the number of variables (p).

Other SLRs could also be developed in order to answer questions not addressed in this review, such as: the disadvantages and limitations of each type of MSPC chart, or which MSPC chart is most suitable for each process (batch, continuous, lots, etc.). Other SLR studies could be conducted focusing on just one type of multivariate control chart, industry sector, or specific distribution type, thus providing an even more detailed study.

Conclusions

This article reports a systematic review of MSPC chart analysis and perspectives in the industrial sector, focusing on articles published between 2010 and

2020. Altogether 51 articles were part of this review. Research in this area has increased in recent years, mainly into the benefits of using MSPC charts. The four key points to be highlighted are:

- The industry type where MSPC charts were most used in the last 10 years was electronic. In the first five-year period (2010–2015) the objective of using MSPC charts in the electronic sector was related to the statistical control of variables linked to the product. However, in the second five-year period (2016–2020), the focus became the control of variables related to the process.
- The MSPC chart most frequently applied in the industrial sector was the traditional Hotelling's T^2 chart, introduced by Harold Hotelling (1947). The Hotelling's T^2 chart is appropriate when it is intended to investigate variations in the mean of interrelated variables. This graph was very flexible, being applied in several industry types: health, construction, metallurgical, electronic, food, textile and energy.
- The normal distribution was the most common distribution in MSPC charts in the industrial sector. Almost half of the combinations between the distribution and the multivariate control charts considered that the data followed a normal distribution. Normality is presupposed for the use of some charts, for example, the generalized variance |S|chart.
- The main research gaps and future research directions are in the combinations of MSPC charts and more comprehensive simulations with a greater number of variables or observations.

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Highlights

- Electronics industry was the one that most used MSPC charts.
- The MSPC chart most frequently applied was the traditional Hotelling's T^2 chart.
- Normal distribution was the most common distribution in MSPC charts.
- Combinations of MSPC charts are the main gaps in future research.