Advances in statistical quality control chart techniques and their limitations to cement industry

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Abstract: Sustainability issues are challenging the cement industry due to its high emission of greenhouse gas, intensive energy consumption, and depletion of resources. One of the strategies to mitigate the problem is to improve process control techniques and optimize resources. The objective of this paper is to survey the approach and evolution of statistical process control chart techniques and study their significance and limitations in the case of optimization of cement production. The main research question this study address is “What are the significances and limitations of statistical process control chart methods to the optimization of cement process?” The methodology of the study followed the literature survey with meta-analysis and focused on identifying the statistical process control chart design techniques and their application to cement industries. The result of the survey indicated that statistical and mathematical algorithms are encapsulated by advanced soft computing methods; however, still, it is the foundation for advanced process control methods. Moreover, it is found that statistical process control has a theoretical and technical gap in the application of the cement industry. The theoretical gap identified in the literature is that in the case of a complex production system the techniques recognize the occurrence of the out-of-control case in the production process but are not able to identify the cause of variation. The technical gap in the statistical process control techniques is that there are several important theoretical control chart techniques, but they are not researched well on how to apply to the real world.

Subjects: Multivariate Statistics; Industrial Engineering & Manufacturing; Civil, Environmental and Geotechnical Engineering

Keywords: Univariate statistical process control; multivariate statistical process control; data mining-based process control; machine learning-based process control; process control in cement industry

1. Introduction

The cement industry is the backbone of the construction sector. Infrastructures like bridges, dams, power stations, hospitals, schools, city development plans, housing programs, industries, and similar mega construction projects are realized due to the supply of cement. Cement demand is increasing every year as a result of industrialization, urbanization, and population growth. Such noticeable consumption growth has changed the lifestyle and quality of life of the population. Furthermore, the construction industry employs a large number of workers. Hence, cement has a significant impact on social, cultural, and economic development.
Currently, the cement industry is challenged by sustainability issues as a result of the high volume of depletion of resources, high energy consumption, and large impact on the environment. Cement is the second most consumed material on the planet next to water, with about 4.10 billion tonnes/year for the year 2018. It is estimated that one-third of the total natural resources consumed by the industries are used for cement production (John et al., 2019). To manufacture one ton of Ordinary Portland Cement (OPC), approximately 1.5 tons of raw materials are required. As a result, the depletion rate of natural resources is increasing exponentially as production volume is increasing every year.

The cement industry is the third-largest industrial energy consumer, with 7% of the global industrial energy use (F.Birol, 2018). Each tone of clinker needs 2800 MJ of thermal energy and 103 to 110KWh of electrical energy. Hence, the energy reduction strategy in the cement industry is the most sensitive issue to sustain in the market.

Cement has emitted about 900 kg of CO₂ to the atmosphere per ton of production of clinker. It is estimated that 8% of global CO₂ emission is from both the chemical decomposition of raw materials and the thermal combustion of fuel to burn the raw material in the production of cement (Poudyal & Adhikari, 2021).

Long-term and short-term strategies are designed to overcome the above challenges faced by cement industries. Large-scale replacement of cement with other binding materials is the long-term strategy. This strategy is applied to pilot projects, and it was successful; however, it cannot be possible to replace the current type of cement in the next decade due to the large volume of global demand per year (Habert et al., 2020). Optimization across the value chain in the short-term strategy aims at reducing CO₂ emission, energy consumption, waste reduction, and optimal raw material consumption (Matthew Carlyle et al., 2000). One of the optimization techniques is statistical quality control (SQC) which applies statistical tools to improve the productivity and quality of the product.

The statistical process control (SPC) charting method is the foundation of SQC which is introduced only a decade ago, while mass production of Portland cement was introduced. Two motives drive us to study SPC as an optimization technique for the cement industry. These are the production system and the technological advancement of the cement industry. Cement production is a complex system. In general, there are five stages to completing the cement production process. These are the raw material preparation stage, raw mix and milling stage, clinker forming stage, cement milling stage, and packing and delivering stage. Each stage comprises many parameters that influence the production system. SPC plays the key role in material selection in quarries: raw material blending according to the raw mix design; optimizing both thermal and electrical energy consumption in the clinker forming stage; maximizing additives to the cement milling stages; and monitoring the compressive strength, fineness, and other product quality parameters.

The cement industry has recorded remarkable technological advancement over the last century. This technological change in types of machinery and control devices has influenced the way SPC is applied to the industry. Online data collection systems, smart sensor and equipment technology, condition monitoring equipment, transformation to digitalization, application of intelligent optimal control and industry 4.0, and decision support systems further drive the application of process control techniques to make the cement production system more productive (John et al., 2019). The technological progress is summarized and presented by Xu et al. (Blezard, 1998) as shown in Figure 1.

Both statistical process control (SPC) techniques and cement production systems are profoundly improved over the last 100 years. However, the authors observed that there are limited publications on the application of SPC techniques to cement industries. The current world demands the
Figure 1. The technical progress of the cement industry since 1887 (Blezard, 1998).

The cement production system to meet environmental, economic, societal, and technological requirements to sustain in the market. Hence, cement industries design strategies to fulfill these requirements and search for opportunities and maximize outcomes from optimization techniques. On the other hand, wide research ideas are introduced on statistical process control like variable sample size and sampling interval methods, economic designs, attribute data methods, charts based on autocorrelated observations, and multivariate and non-parametric methods as well discussed in the literature reviewed in this paper. Hence, the following research questions are raised to examine this topic. What are the basic researches done on statistical process control chart design techniques? Which direction the basic research is proceeding? Do these basic research findings satisfy the demand of cement industries? The main objective of the research is then to survey the advances of statistical process control chart techniques over the last century and investigate how far they can fill the demand of the cement industries.

2. MATERIALS AND METHODS

2.1. Data selection

This paper collected and analyzed the relevant articles on statistical control chart design techniques and their application to cement industries. The literature survey uses a meta-analysis method to filter articles. The data sources were mainly Scopus, Web-of-science, ScienceDirect, IEEE Xplore, JSTORE, Google Scholar, and Taylor and Francis databases. The preliminary survey of the literature indicated that process control chart techniques have passed four steps. These are univariate statistical process control, multivariate statistical process control, data mining, and machine learning.

Then, the search methodology that leads to the identification of the set of papers is based on the following keywords: univariate statistical process control, multivariate statistical process control, data mining, machine learning, and process control in the cement industry. A general overview of the flow of the search method is plotted in Figure 2.

2.2. Data collection and analysis

Data collection has started firstly to answer the foremost research question. Do we need to research the application of statistical process control in the cement industry? To answer this question, articles on each technique and the application of these techniques in the cement
industry have been searched on the Scopus database since the 1980s. The literature is then analyzed based on publication years, and the result indicated that the number of research articles published on the application of SPC to cement process control is almost nil as shown in Figure 3. This implies that study in this direction is not well researched.

Extracting relevant articles in line with the next research questions, i.e. “What are the basic researches done on statistical process control chart design techniques? Which direction the basic research is proceeding? Does the research on statistical process control answer the demand of cement industry? “generates bulk data. Hence, filtering the most important articles is assisted by VOSviewer software.

The following search queries are used for the first identified keyword.

TITLE-ABS-KEY (univariate AND statistical AND process AND control).

Scopus database generates 654 documents. Search this keyword for other databases and then collect the documents into the same folder. Use inclusive and exclusive criteria like the language of the document, subject area, and keywords to the specific area and reduce the number of
documents. Using the type of analysis co-citation and unit of analysis cited-authors in the VOSviewer software, the most influential authors in the univariate statistical process control chart techniques are identified as shown in Figure 4.

Follow the same procedure to the second identified keyword.

TITLE-ABS-KEY (multivariate AND statistical AND process AND control).

Scopus database generates 4409 documents. The most influential authors in the multivariate statistical process control chart techniques are identified as shown in Figure 5 and 6. This figure indicated that some of the researchers who have introduced univariate SPC techniques are also mentioned in MSPC techniques.

Follow the same procedure to the third identified keyword.

TITLE-ABS-KEY (data-mining AND statistical AND process AND control).

Scopus database generates 876 documents. And the result will be observed in Figure 7.

The fourth keyword in the literature survey is machine learning. From the preliminary literature review, it is identified that machine learning techniques can be categorized into seven groups. These are supervised learning, semi-supervised learning, unsupervised learning, reinforcement learning, ensemble learning, instance-based learning, and multitask learning. For each technique that belongs to a single group, documents are identified following the same procedure as indicated above. For example, support-vector-machine is one of the supervised machine learning techniques. The following keywords are used to search the articles.

TITLE-ABS-KEY (support AND vector AND machines AND pattern AND recognition). The result will be shown in Figure 8.

Figure 4. Highly cited authors in Univariate SPC.
Finally, after reviewing the full documents, a total of 135 articles are selected as references for this literature survey.

3. Statistical process control techniques

Statistical process control (SPC) has played a major role in monitoring, controlling, and optimizing the production system. SPC has improved the quality of the product and productivity of the plant. It demonstrates how consistently the process is performing. Control charts display undesirable
variation due to assignable causes. Formally, SPC is defined as the monitoring and analysis of process conditions using statistical techniques to accurately determine process performance and prescribe preventive or corrective actions as required.

The advancement of the SPC techniques can be categorized into four periods. The first and the second periods are represented by statistical-based process control techniques. The first period started at the beginning of the 1920s. During this time, the II industrial revolution has immersed which was characterized by the introduction of mass production. The shift from batch to mass production has increased the production volume. As a result, process control techniques were changed from manual inspection to sampling scheme and univariate SPC charts. The second period was introduced during the 1950s when the Second World War exploded. This period was characterized by extremely increasing production volume and highly demanding precision work. During this time, multivariate statistical process control techniques were presented.

The third and fourth periods are represented by non-statistical-based process control techniques. The third period was introduced during the middle of the 1970s. This is the time when the III industrial revolution was introduced. This time is marked by the introduction of computers and sensors to automate production systems. Due to abundant information accumulated in a database within a short period, data mining techniques to monitor the production system have dominated the process control techniques. Engineering process control and statistical process control methods were reinforced by each other during this time. The fourth period was introduced in the middle of the 1980s. Machine learning is introduced into the production system. Algorithms are developed that can train the machine to learn from the environment. The following sub-sections discuss separately each period of the development.

3.1. Univariate statistical process control (USPC) techniques

In the first period, rigorous mathematical and statistical analyses were applied to design the procedures and to detect changes in a process over time. The concept of statistical process control (SPC) was invented and introduced by Shewhart in 1924. The first article on this topic was published in 1926 (Shewhart, 1926). Shewhart promoted further the importance of control charts in quality concept by publishing two books; “Economic Control of Quality of Manufactured Product” (Shewhart, 1931) in 1931 and “statistical method from the viewpoint of quality control” written by Shewhart and Deming in 1939 (Shewhart & Deming, 1939). Western Electric Company has strengthened the work of Shewhart by publishing the statistical quality control handbook in 1958 (Electric, 1956).

Shewart has implemented the theory of distribution and sampling schemes in his control chart design. The model assumes the data distribution to be normal. There are three design parameters,
“sample size”, “sampling interval”, and “width of control chart”. The statistical criteria determine the appropriate control limits through the specification of a maximum probability of a type I error (False alarm) and/or a type II error (failure to sound an alarm). The control chart which is the graphical display of quality characteristics can be considered as a test of the hypothesis that the process is in the state of statistical control. A point plotting within the control limits is equivalent to failing to reject the hypothesis of statistical control, and a point plotting outside the control limit is equivalent to rejecting the hypothesis of statistical control (Murthy & Rambabu, 1997).

The heuristic approach to Shewhart control chart design is the simplest control chart design that considers statistical criteria and practical experience that recommends the use of samples of size 5, three sigma control limits, and a sampling frequency of 1 h for the $\bar{X}$-charts. Such a control chart was an effective tool to monitor variability in the parameters and display patterns of the process. The control chart patterns can be normal, increasing trend, decreasing trend, cyclic, systematic, mixture, upward shift, and downward shift patterns. Only the normal pattern is consistent with the hypothesis that the process continues to operate without assignable causes, and all other patterns are not and should not be considered unnatural.

The improvement to the Shewhart control chart was introduced by Duncan (Flaig, 1991) referred to as an economic model for the design of the Shewhart type $\bar{X}$-chart. The best selection of sample size, sampling interval, and control width considered the various risk and cost factors and it depends on several process variables like frequency of occupancy of a shift in the process, cost of sampling and inspection, penalty cost of defectives, probability of false alarms, cost of investigation for finding the assignable cause, and process correction costs are considered. Duncan (Duncan, 1971) also considers the case for the occurrence of several assignable causes in his paper and a general model has been developed to determine the total cost as a function of these parameters. Gibra (1975), Montgomery (1980), Lorenzen and Vance (1986) and Ho and Case (1994) presented literature survey on economic design of control charts. The general model for the economic design of control charts has been proposed by Lorenzen and Vance (1986).

Saniga (Saniga, 1989) proposed an economic statistical control chart design where he placed statistical constraints on economic models to provide designs that meet the industry's demand for low process variability and long-term product quality. It was an improvement to statistical design and more costly than economic design but ensures long-term product quality and reduction of the variance of the distribution of the quality characteristics.

Research has also proposed the adaptive control chart design. In this model, one or more design parameters are allowed to vary as a function of process data. These control charts are designed based on statistical criteria, economical or economic statistical criteria. The summary of the selected literature review is presented in Table 1.

The Shewhart $\bar{X}$-control chart has a limitation which is less sensitive to small and medium process shifts; as a result, cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) were introduced. It is noted that Shewhart’s control chart for the mean is very efficient if the magnitude of the shift is 1.5σ or larger (Montgomery, 2009).

Page (1961) has introduced one- and two-sided CUSUM procedures for detecting small mean shifts. In this procedure, called tabular or logarithmic, the cumulative sum of the differences between the sample means and the reference value k of all the previous data are plotted against sample numbers. If it reaches some value H, called decision interval, then the corrective action is to be taken. Hence, CUSUM analysis has a kind of “memory”. He has further presented the concept of average run length (ARL), which is defined as the average number of the samples taken before
the out-of-control signal. Analytical studies were conducted to select the parameters $K$ and $H$ to provide good ARL performance.

An alternative approach to designing a CUSUM chart was introduced by Bernard (Page, 1961) and referred to as a v-mask. The performance of the v-mask is determined by the distance “d” ahead of the leading point and the angle “a” between each of the arms of the V and the horizontal. A Modified V-mask consisting of a parabolic-shaped mask was presented by Lucas (1973,1976). Ewan and Kemp (1960) and Kemp (1962) gave nomograms relating $L$, $h$, and $e$ for normally distributed variables.

CUSUM has been studied by many other authors, in particular Ewan and Kemp (1960), Page (1961), Kemp (1962), Beattie (1962), Ewan (1963), Lucas (1976), Hawkins (1981, 1993), Gan (1991), and Woodall and Adams (1993). CUSUM techniques were reviewed by Bissell (1969). These researches showed that the CUSUM control chart is much more efficient than Shewhart’s $\bar{X}$ control chart for detecting smaller variations in the average. Cumulative sum control (CUSUM) charts are widely used in industry because they are powerful and easy to use. It quickly detects the process which is out-of-control situations (Koshti, 2011) and helps to take corrective actions on the process.

The economic design of the CUSUM chart was first studied by Taylor and Taylor (1968). Goel & Wu (Goel & Wu, 1973) and Chiu(Chiu, 1974) proposed similar models and algorithms for determining the economically optimum design of CUSUM charts and reported some results of sensitivity analysis.

Research also proposed the adaptive control chart design for cumulative sum charts. VSI CUSUM charts were presented by Reynolds et al. (1990) and Reynolds (27,59,60). VSS CUSUM charts were studied by Anandi et al. (Keats et al., 1995). VSSI CUSUM is studied by Arnold and Reynolds (2001).

The other method of univariate statistical process control is the geometric moving average chart. It was introduced by Roberts (1959). Later, it is termed exponentially weighted moving average (EWMA). The statistical design of EWMA control charts with estimated parameters was

### Table 1. Adaptive control chart literature

| Type                                      | Statistical criteria                                           | Economical criteria                                    | Economic statistical criteria |
|-------------------------------------------|----------------------------------------------------------------|---------------------------------------------------------|-----------------------------|
| Variable sampling size (VSS)              | Flag(Flag, 1991), Daudin(Daudin, 1992), Prabhu et al.(Prabhu et al., 1994), Costa(Costa, 1994), Zimmer et al.(Zimmer et al., 1998), Castagliola et al.(Castagliola et al., 2011) | Flag(Flag, 1991), Park and Reynolds(Park & Reynolds, 1994) |                             |
| Variable sampling interval (VSI)          | Reynolds et al.(Reynolds et al., 1988), Reynolds(Reynolds, 1989), Runger and Pignatiello(Runger & Pignatiello, 1991), Zhang et al.(Zhang et al., 2012) | Das & Jain(Das & Jain, 1997), Bai and Lee(Bai & Lee, 1998), Reynolds(Reynolds, 1989), Yu et al. (Yu et al., 2007) | Lee et al.(Lee et al., 2016) |
| Variable sampling size and sampling interval (VSSI) | Prabhu et al.(Prabhu et al., 1994), Costa(Costa, 1997), Carot et al.(Carot et al., 2002) | Park and Reynolds(Park & Reynolds, 1999), | Prabhu et.al (Prabhu et al., 1997) |
| Fully adaptive (VP)                      | Costa(Costa, 1999)                                              | De Magalhaes et al. (2001), Costa and Rahim(Costa & Rahim, 2000) | De Magalhaes et.al (De Magalhaes et al., 2002) |
designed by Reynolds and Arnold (2001) and Jones (2002). The economic design of EWMA charts was proposed by Montgomery et al. (1995) and Park et al. (2004). The economic-statistical design of EWMA charts for control procedure is proposed by García-Díaz and Aparisi (2005).

The adaptive control chart design for EWMA is proposed by researchers. VSI EWMA charts were presented by Sacucci et al. (Sacucci et al., 1992), Reynolds(1995,1996a,1996b). VSS EWMA charts were studied by Reynolds and Arnold (2001). VSI EWMA was studied by Reynolds and Arnold (2001).

Nantawong et al. (1989) experimented to evaluate the effect of three factors (sample size, sampling interval, and magnitude of shift) on three control charts, namely Shewhart, CUSUM, and geometric moving average charts, using profit as the evaluation criteria but without optimizing any of the three charts. Ho and Case (1994) have undertaken a brief economic comparison between Shewhart, CUSUM, and EWMA charts, and they concluded that both CUSUM and EWMA charts have a much better economic performance than Shewhart charts.

3.2. Multivariate Statistical Process Control (MSPC) techniques

Research indicated that the application of univariate SPC charts for each variable in the production system can be misleading to the monitoring result because such charts do not consider the correlation effect between variables. Hence, designing MSPC charts becomes one of the active research areas in SPC.

The multivariate technique was first developed as an extension of the Shewhart control chart by Hotelling in 1947. In his earlier work (Hotelling, 1925), he generalized the Fisher-Student t-test to more than one dimension for the analysis of variance. Then, the result was found to be suitable for industrial quality control and sampling inspection problems in the case of multivariate measurements.

Consequently, MCUSUM and MEWMA were developed in the 1950s through extensions of CUSUM and EWMA. The Hotelling $T^2$, multivariate cumulative sum (MCUSUM), multivariate exponentially weighted moving averages, projection-based methods such as principal component analysis (PCA), and partial least square (PLS) are the types of statistical-based MSPC methods.

Similar to univariate SPC methods, their multivariate extensions were also studied based on statistical, economical, and statistical-economical design approaches. Several authors have investigated the economic design of multivariate $T^2$ control charts. Initial work in this area includes Montgomery and Klatt (1972), Heikes et al. (1974), and Alt (1976).

The MCUSUM control chart was first proposed by Woodall and Ncube (1985). Then, Crosier (1986,1988) proposed two MCUSUM control charts, CUSUM of $T$(COT) statistics schemes, and a CUSUM vector scheme. Healy (1987) applies the CUSUM procedure to the multivariate normal distribution for detecting a shift in the mean vector or for detecting a shift in the covariance matrix. Pignatiello and Runger (1990) also propose two MCUSUM charts, namely MC1 and MC2. The first multivariate CUSUM chart (Multivariate CUSUM #1) accumulates the observations before producing the quadratic forms of the mean vectors, while the second multivariate CUSUM chart (Multivariate CUSUM #2) calculates the quadratic form of each observation and then accumulates the quadratic forms of the mean vectors.
The optimal statistical design of the MCUSUM chart for multivariate individual observations based on average run length (ARL) and median run length (MRL) was proposed by Lee and Khoo (2006). An Economic-Statistical design of the MC1 control chart was proposed by Saraie (2007).

The MEWMA chart was introduced by Lowry et al. (1992) as an extension of the univariate EWMA chart. Prabhu and Runger (1997) proposed the statistically designed MEWMA charts. Linderman and Love (2000) proposed methods to design the Economic & economic statistical design for MEWMA control charts. Molnau et al.(Molnau et al., 2001) presented the statistically constrained economic design of the MEWMA control charts.

Principal component analysis (PCA) and partial least square (PLS) are introduced to overcome the dimensionality and collinearity problems faced by Hotelling $T^2$, MCUSUM, and MEWMA. PCA reduces the dimensionality of a dataset with a large number of correlated variables into orthogonal less-dimensional latent variables (Kazmer et al., 2008). PLS considers the latent structure of both the process variables and product quality characteristics. MSPC based on PCA was presented by Ferrer (2007) and Braga et al. (2018). MSPC based on PLS is presented by MacGregor and Kourtì 1995 and Kresta et al. (1991).

3.3. Data mining based MSPC

As technology advanced over time, limitations of MSPC techniques were observed. The rigorous mathematical and statistical analyses of the procedure, its time-consuming process during analysis, and unsuitable for complex, non-linear, and non-parametric problems found to be not convenient for industrial applications. As a result, advanced process control techniques like data-mining are introduced.

Data mining refers to the analysis of large quantities of data that are stored in computers (Olson & Delen, 2008). Data mining is a wide discipline concerned with the extraction of implicit and potentially useful information from data, by searching for patterns and relationships hidden in the data(Zaiane, 2002). Technological advancement in data collection and analysis by computers pushes the statistical analysis from the traditional MSPC methods to the data mining stages. The large volume of data sets recorded in the modern database, less influenced by outlier detection and missing data, nonstationary of the population, i.e suitability of online data analysis with varying population, extracting data patterns quickly and efficiently, and deals with non-numerical data make data mining more preferable (Hand, 1998).

Zaiane (2002) classifies Data Mining methods into five major categories such as classification, deviation detection, clustering, association, and sequential patterns. To list some of the traditional data mining techniques studied under these categories are Decision trees (DT), Neural Networks (NN), KNN (K nearest neighbor), support Vector Methods (SVM), Genetic algorithms, fuzzy data mining approach, and rough set methods. Literature indicated that almost all of the data mining techniques outperformed the traditional MSPC approaches in out-of-control detection (Mason & Young, 2002).

Support Vector Machine (SVM) is one of the widely researched data mining techniques introduced by Vapnik(Vapnik, 1998). Tax and Duin (2004) proposed the Support Vector Data Description (SVDD) which is inspired by support vector data classification. Schölkopf et al. (2001) introduced one-class support vector machine (OCSVM). Sun & Tsung (2003) proposed a support vector data description (SVDD) based control chart which is called K-charts. K-chart refers to kernel distance-based multivariate SPC. The industrial application of the k-chart is sensitive to small shifts in the mean vector and outperforms the $T^2$ control chart in terms of ARL(Gani et al., 2011). Ning and Tsung (2013) provided an optimized design method for the SVDD-based K-chart.
Cai (2006) proposed support tensor machine. Chen et al. (2016) suggested the one-class support tensor machine (OCSTM) which extends one-class support vector machine (OCSVM) to take tensors as input data. Sukchorat et al. (2010) proposed one-class classification-based control chart for multivariate process monitoring. Maboudou-Tchao suggested SVDD control chart using Mahalanobis kernel (Maboudou-Tchao et al., 2016), control chart based on support matrix data description (SMDM; Maboudou-Tchao, 2017) and support tensor vector data description (Maboudou-Tchao, 2019).

He and Zhang (S. S. He & Zhang, 2011) proposed the support vector data distribution (SVDD) based MCUSUM chart, referred to as S-MCUSUM. The research compared the proposed technique with the Crosier COT chart. This control chart has the advantage of analyzing free distribution. In their simulation model, they have shown that the S-MCUSUM chart outperforms the COT chart under banana-shaped distribution which is typical of free distribution.

Xia et al. (2018) proposed a D-MCUSUM control chart which is designed from the modified multivariate CUSUM control chart based on support vector data description (SVDD). It has the advantage of high sensitivity to small shifts from the multivariate CUSUM algorithm and learning abilities from support vector data description algorithms.

3.4. Machine learning (ML)
Another method developed regarding the advancement of production technology and innovation is machine learning. Machine learning is used to teach machines how to handle data more efficiently (Dey, 2016). Machine learning algorithms can be categorized into supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, multitask learning, ensemble learning, and instance-based learning.

In supervised learning, instances are given with known labels (corresponding correct output) and then the learning is the search for algorithms to produce general hypotheses which then make predictions about future instances (Kotsiantis, 2007). Decision Tree, Naïve Bayes, support vector machine, and Neural Network are types of supervised learning.

The decision tree algorithm classifies the instances by sorting based on feature values (Kotsiantis, 2007). Quinlan (Quinlan, 1993) developed an algorithm that creates a separate rule for each path from the root to a leaf in the tree and then the decision tree is translated into a set of rules. The rules can also be directly induced from training data using a variety of rule-based algorithms. The naïve Bayes machine learning algorithm is based on the theorem of probability proposed by Thomas Bayes in the 1740s. Support Vector Machine (SVM) was proposed by Vapnik (Boser et al., 1992). This technique has a satisfying theoretical background and solves a variety of learning, classification, and prediction problems.

Unsupervised learning is the type of learning where the training data set consists of only a set of input vectors X and no available output observation. Then, from this row of a dataset, the useful information is extracted. Clustering and principal component analyses (PCA) are the two most popular unsupervised learning. Cluster analysis is the formal study of algorithms and methods for grouping or classifying objects (Jain & Dubes, 1988). K-means clustering is a type of clustering where the algorithm works iteratively to assign each data point to one of the k-groups based on the features that are provided.

Semi-supervised learning algorithms are techniques that combine the power of both supervised and unsupervised learning. It contains both labeled and unlabeled data where the labeled data are small in number and unlabeled data are by far large in number. Generative models, self-training,
co-training, transductive support vector machines (TSVM), and reinforcement learning are the types of semi-supervised learning algorithms.

Reinforcement learning (RL) is a recently introduced machine learning technique to process control. Viharos and Jakab (2021) presented the application of RL for statistical process control in manufacturing. In this research, in addition to the necessary elements in RL (Sutton et al., 1992), novel techniques called dynamic Q-Table, epsilon self-control of exploration–exploitation ratio, reusing window (RW), and the measurement window (MW) are introduced. Bagdwell (Shin et al., 2019) proposed a promising research direction for the integration of RL and Model Predictive Control (MPC) for a better decision support system to process control. Spielberg et al. (2019) have developed adaptive deep reinforcement learning (DRL) by combining reinforcement learning and deep learning.

Another method of machine learning is instance-based learning. This method is the improvement of supervised machine learning in that it stores and uses specific instances that generates classification predictions (Aha et al., 1991). One of the instance-based learning algorithms is the K-nearest neighbor algorithm (K-NN). K-NN is based on the principle that the instances within a dataset will generally exist close to other instances that have similar properties (Cover & Hart, 1967). The classification is conducted by first calculating the distance between the test sample and all training samples to obtain its nearest neighbors and then conducting K-NN classification. A review of instance-based selection methods is presented by Olvera-López et al. (2010). A good performance of the application of the K-NN algorithm to fault detection in process control is presented by Verdier and Ferreira (2011) and He and Wang (2007).

In some cases where the general learning tasks like supervised tasks, unsupervised tasks, semi-supervised tasks, and reinforcement learning tasks are related to each other, learning these tasks jointly improves the performance compared to learning individually (Caruana, 1997). Such a type of simultaneous learning while tasks are trained in parallel is called multitask learning. Formally, multitask learning is defined as follows: Given m learning tasks \( \{T_i\}_{i=1}^m \) where all the tasks or subsets of them are related, multitask learning aims to help improve the learning of a model for \( T_i \) by using the knowledge contained in all or some of the m-tasks (Zhang & Yang, 2018).

Last but not least, machine learning method is ensemble learning. An ensemble consists of a set of individually trained classifiers whose predictions are combined for classifying new instances. The first ensemble method was introduced by a composite system design of linear and nearest neighbor classifiers to meet the performance criteria of the maximum computational economy with minimum loss in recognition accuracy (Dasarathy & Sheela, 1979). Polikar (2006) categorizes the two types of combination by ensembles; these are classifier selection and classifier fusion. In classifier selection, each classifier is trained to become an expert in some local area of the total feature space, whereas in classifier fusion all classifiers are trained over the entire feature space. Bagging and boosting are two of the many approaches to ensemble learning that belongs to classifier fusion. AdaBoost, stacked-generalization, and mixture-of-experts have also belonged to the variations of ensemble learning.

Recent research indicated that machine learning techniques are also continuing to solve the problem faced by MSPC charts. Shao and Lin (2019) proposed a time-delay neural network approach to diagnose the small number of quality variables that cause out-of-control signals for a multivariate normal process with variance shift. Then, they have compared their results with artificial neural network (ANN), support vector machine (SVM), and multivariate adaptive regression splines (MARS) classifiers. Finally, they proposed a future research direction for a large number of quality variables.
4. SPC methods applied in cement industries

Statistical process control is the conventional method applied to cement industries to monitor, control, and improve the production processes. Such applications optimize the consumption of resources like raw materials and energy and reduce emission gases. Cement consumes energy intensively. As a result, one of the strategies of cement industries is to reduce both thermal and electrical energy consumption by implementing different energy-saving actions.

Efkhami (Afkhami et al., 2015) applies CUSUM to identify changes in historical energy performance patterns. His research studies the different energy-saving actions like leveling the kilns, sealing the gaps and holes, cooperation between labs, mine and production units, replacement of primary air fans, replacement of cooling towers pumps, and installing the vertical shaft impactors, and the CUSUM chart indicates that the slope is going steadily down for the study period and confirms that there is steady saving. Moreover, the critical points can also be identified in which the slope varies.

Castañón et al. (2015) apply the multivariate PLS method to study energy and environmental saving by identifying important kiln parameters that most influence clinker quality. The study focuses on 23 kiln operation parameters and 8 clinker quality parameters and the optimal intervals to improve the process are identified. Finally, the amount of fuel-saving was calculated, and a reduction in CO₂ emission was estimated. Bakdi et al. (2017) introduced a new monitoring scheme based on PCA with an EWMA-based adaptive threshold to monitor kiln operation. Moses and Alabi (2016) proposed a regression-based model to predict clinker quality parameters.

Wang et al. (2016) have performed research that applies data mining techniques to predict the pozzolanic activity (PA) of solid wastes. In their research, artificial neural network (ANN) and time-series models are applied to predict the PA of 22 types of solid waste materials with diverse physicochemical properties that underwent combustion, other heating, and pretreatment before they were blended as pozzolans with cement. Blending these materials with cement saves raw materials, fuel and energy use and achieves equivalent or superior concrete properties.

Yao et al. (2021) proposed an incremental deep dynamic feature extracting and transferring model to predict the free-CaO content of cement clinker. Pani and Mohanta (2016) proposed a feed forward artificial neural network and fuzzy inference model to predict eight clinker quality parameters (free-lime, lime saturation factor, silica module, alumina module, alite, belite, aluminate, and ferrite). Ateş et al. (2021) studies artificial intelligence-based decision support systems for the sustainable eco-friendly cement production system. In this research, the activity index of ground granulated blast furnace slag (GGBS) used as cement and concrete additives are predicted using an artificial neural network (ANN) and adaptive neuro-fuzzy interface system (ANFIS).

5. Conclusion

Cement is produced in a continuous fashion and under different constraints. Raw materials have to be proportionally mixed; clinker quality parameters must be kept in the standard; the final product, i.e., cement, should meet the quality requirements; electrical and thermal energy consumption should be optimized; equipment life is to be prolonged, and environmental pollution should be minimized. The research aimed to review the process control literature and investigate how far process control techniques are applied to the cement industry and then further scrutinize the gap the process control techniques have not fulfilled in the demand of the cement industry. Several statistical process control methods are developed since the introduction of process control techniques in the 1920s. The promising techniques that simultaneously search for optimal solutions are conducted by MSPC, data mining and machine learning. However, it needs further research in this sector.
The trend of publications over time indicated that the research direction of industrial process control has advanced in the sequence of univariate statistical process control, multivariate statistical process control, data mining-based process control, and finally machine learning-based process control. In the univariate and multivariate statistical process control, there is rigorous statistical and mathematical analyses. Statistically based data mining techniques have mixed traditional process control techniques with information extraction algorithms developed by computer scientists for bulk databases. Meanwhile, machine learning techniques have come with the new philosophy of learning algorithms. Each group of techniques has its strength and weakness. For instance, the applications of mathematical and statistical theories, like distribution theories, in the conventional statistical process control methods can never be achieved by the algorithms developed by machine learning. On the other hand, the conventional statistical process control methods are time-consuming and need statistical knowledge to apply in the production process. Furthermore, features from big data can be easily extracted by data mining and machine learning algorithms but not by conventional SPC methods. Hence, the trend of publications over time does not imply that the earliest research methods on SPC are replaced by recent ones.

The literature review of the process control techniques revealed that several statistical procedures are not implemented in cement industries but, if they are implemented, can improve the productivity of cement plants. It is observed that vast research ideas are proposed on the topic of economical, economical-statistical, variable sampling size and sampling interval procedures. Currently, cement industries are implementing fixed time sampling interval procedures. This implies that there is a need to extend the research on how to apply these ideas to cement industries in such a way that the industries can utilize them for the optimization of resources.

Cement industries are introducing Industry 4.0. As a result, process control techniques are influenced by the digital revolution. Process data is no more the production data alone. All data are collected and then connected to the central control system. The current state of the art in process control is also directed towards this end. Hence, it is expected that data mining and machine learning would be the standard process control techniques. However, there are traditional laboratory activities in cement industries like sampling, analytical, physical and mechanical tests. To overcome the delay of these test results, the concept of soft sensors is developed from previous test results. Hence, process control techniques are going to be dependent on data analysis collected from hard and soft sensors.

6. Limitations and future research direction
The fierce competition in the cement industries, rules and regulations for environmental protection, the increasing amount of energy consumption as a result of increasing production volume, and higher depletion of raw material resources are challenging the cement industries. Optimizing the system is one of the solutions to these problems. Process control is one of the promising optimization techniques. However, currently, the demand for cement industries exceeds the capability of the available process control techniques. A good example is that in the case of multivariate processes, the process control techniques can recognize the presence of outliers but are not able to identify the variables that cause the problem. There are efforts to solve this problem in the MSPC, data mining and machine learning areas but remains to be the research topic. Hence, basic research will be continued to solve the real problems faced by cement industries.

A literature review of statistical process control methods in the case of cement production systems indicates that the direction of research is driven from statistical-based methods to data mining and machine learning algorithms. Some of the data mining techniques incorporate both the statistical and information extraction algorithms from bulk data. On the other hand, the machine learning methods depend on learning algorithms. Methods like decision tree, reinforcement learning, and Artificial
Neural Network may not need bulk data like data mining and do not intensively apply statistical theories but depend on the logical relationship of data. Hence, comparing performance between data mining and machine learning remains to be the research gap not covered by the literature.

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