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Effective monitoring of carbon emissions from industrial sector using statistical process control

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HIGHLIGHTS

- A scheme for effective monitoring and controlling of carbon emissions is proposed.
- The scheme is optimized for detecting increasing shifts in carbon emissions.
- Effectiveness of the proposed scheme is investigated under different scenarios.
- Continuous monitoring of carbon emission reduces the related costs significantly.
- Valuable insights are provided for designing the proposed monitoring scheme.

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ABSTRACT

The industrial sector is considered one of the fastest-growing sources of greenhouse gases, due to the excessive consumption of energy required to cope with the growing production of energy exhaustive products. The statistical process monitoring (SPM) can be an effective tool for monitoring and controlling carbon emissions from industries. This article presents an economic-statistical design of the combined Shewhart $\overline{X}$ and exponentially weighted moving average (EWMA) scheme ($\overline{X}$&EWMA scheme) for monitoring carbon emissions from industries to allow prompt action for controlling excessive emissions. The parameters of the proposed SPM scheme have been optimized for minimizing the expected total cost, including cost from carbon emissions and operational costs of the SPM scheme. The design of the $\overline{X}$&EWMA scheme has been optimized considering a wide range of shifts in the mean of the emission process, and ensuring that the constraints on inspection rate, sample size, and false alarm rate are all satisfied. Comparative studies showed that the optimal $\overline{X}$&EWMA scheme reduced the expected total cost by about 40%, 77%, and 28% compared with the basic $\overline{X}$, EWMA, and $\overline{X}$&EWMA schemes, respectively. The impact of the design parameters on the effectiveness of the proposed SPM scheme has also been investigated by sensitivity analysis. Finally, the application of the proposed SPM scheme is demonstrated by using real data for carbon emissions from different industrial facilities. This study is expected to considerably reduce the cost owing to excessive carbon emissions from industries and widen the literature on the utilization of SPM tools in managing the quality of the environment.

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1. Introduction

Environmental degradation is considered as one of the most critical issues by today's researchers, professionals, and policymakers. Human activities increase the emission of heat-trapping gases, known as greenhouse gases (GHGs) that cause global warming and ecological imbalances [1,2]. Uprety et al. [3] reported that the concentration of GHGs in the Earth's atmosphere has significantly increased since the pre-industrial era of 1850. This increase of GHGs emissions is changing the Earth's climate, leading to various catastrophic events such as floods, earthquakes, droughts, and the deterioration of the polar regions [1]. According to the Kyoto Protocol, carbon dioxide (CO_2) is one of the six major GHGs that potentially influence the climate [4].

Since 1990, the industrial sector has grown by 174% and is considered the fastest-growing sources of GHGs [5]. Carbon emissions from different industrial sectors are characterized by a wide range of emission quantities, depending on the type of industrial sector, the type of technology used, and the energy source. Although energy consumed by different industrial sectors has decreased in recent years, the total energy use has still increased due to production growth and the increase of energy exhaustive industrial products [6]. The International Energy Agency (IEA) presumes that industrial energy use will continue to increase until it approximately doubles in 2050, as compared to the consumption levels in 2009. As a result, the industrial CO_2 emissions are expected to increase by 45–65% [6]. Chontanawat [7] investigated the dynamic relationship between energy consumption and carbon emissions using co-integration and causality models, and concluded that energy consumption causes carbon emissions, implying their increases are directly proportional to each other. Thus, monitoring carbon emissions is the key towards encouraging households, businesses, and industries to use energy-efficient products as well as clean energy.

Many industrialized countries have imposed environmental legislations or carbon taxes and/or implemented the cap-and-trade system to control fossil fuel emissions and promote cleaner energy [8–10]. The carbon tax is a surcharge applied on GHGs emissions, mainly from burning fossil fuels. For instance, Sweden has imposed a carbon tax since 1991 to minimize GHGs emissions, and the federal government of Canada has been enforcing rules and regulations nationwide to ensure all provinces have a carbon fee in place. On the contrary, in a cap-and-trade system, governments put a threshold or cap on the average amount of carbon emissions from an industry. The United States and the European Union have been successfully implementing the cap-and-trade system to meet the commitments toward controlling GHGs emissions [11,12].

However, researchers are continuously exploring varying techniques to find the most effective way to control carbon emissions. Chen et al. [13] proposed an inexact multi-criteria decision-making model for ensuring the optimal lifecycle economics and GHGs emissions under uncertainty. To promote sustainable development of human society, the transition of the global energy system from high-carbon to low-carbon energy resources, such as shale gas, is essential. Chen et al. [14] developed a multi-level programing model for lifecycle assessment of GHGs emissions and water-energy optimization for a shale gas supply chain. Similarly, He et al. [15] evaluated shale gas resources and their corresponding environmental implications under uncertainty. Abeydeera et al. [16] emphasized on monitoring and documenting the amount of carbon emissions at various levels (product, organization, city, and country) with the objective of formulating the necessary strategies to manage the quality of the environment. Likewise, [17] and [18] developed systems for monitoring and assessing the environmental performance of the real estate sector in Sweden via environmental indicators. They concluded that the energy and emissions of buildings can be estimated using time series models. According to [19], analyzing the patterns of the recently monitored data of carbon emissions can be very beneficial to efficiently assess current and future carbon emission trends. Thereafter, many studies have been directed to evaluate the emission rates from different industries, such as manufacturing [20] and energy [21]. In addition, statistical process monitoring (SPM) schemes can be used successfully to continuously monitor the emissions data and identify unusual changes in a timely fashion [22–24].

The continuous monitoring of carbon emissions from industries using SPM schemes can provide several benefits. At the industrial level, it can help in identifying excessive emissions at an early stage, and thus ensure that appropriate action can be taken in advance to control them, which in turn can minimize the expected total cost including emission-related and operational costs of the SPM scheme. For policymakers, it can assist in (i) evaluating whether the emissions are within the regulatory limit (e.g., carbon-cap as specified by the government) or at a high risk of non-compliance, (ii) adjusting the control parameters in a systematic way to avoid non-compliance, (iii) monitoring and measuring the impact and related costs of emissions on the environment, (iv) establishing guidelines for evaluating real-time emissions against the targeted emissions and regulatory requirements, and (v) deciding which facility needs more frequent inspection, based on the frequency of the signal produced by the SPM schemes. Most importantly, SPM schemes can help decision-makers set an appropriate amount of emission fee (i.e., carbon tax).

The remainder of the paper is organized as follows. Section 2 reviews the relevant articles, identifies the research gaps, and highlights the contribution of the paper. Section 3 develops the model for the optimization design of the proposed SPM scheme. Section 4 discusses the results of numerical studies conducted to evaluate the performance of the proposed SPM scheme under different operational scenarios. Section 5 illustrates the design and application of the proposed SPM scheme through a case study. Finally, the conclusions and future research directions are discussed in Section 6.

2. Literature review

The SPM tools have been mainly applied for measuring and controlling the quality of products in manufacturing industries for over 50 years, where the SPM chart is commonly used for monitoring a manufacturing process behavior over time to identify any unusual changes or trends, which ultimately helps in reducing the waste and improving the quality of the product [25]. The widespread application of SPM charts in manufacturing is mainly due to the fact that the quality characteristics (e.g., dimensions of a product) in a manufacturing setting can easily be defined and measured. Moreover, the flow of the products throughout most of the manufacturing processes can easily be tracked and controlled. On the other hand, the application of SPM tools in non-manufacturing sectors is really challenging because of the invisible work processes, lack of data, and difficulties in standardizing and measuring the quality characteristics. Although the application of SPM charts is comparatively less in non-manufacturing sectors, its adoption is growing rapidly because of the significant improvement in data acquisition and powerful computing systems in the recent years. One such sector is the environmental quality management (EQM). The quality of environment (e.g., quality of ambient air) can be affected by different sources, including carbon emissions from industrial facilities. Few researchers have proposed the application of SPM charts for controlling and managing the quality of environmental processes through the effective monitoring of environmental characteristics, such as pollutants discharged from different industries into the environment (for instance, see [26,27]). Madu [26] explained how SPM schemes can be used for environmental monitoring, while [22] designed a traditional cumulative sum (CUSUM) chart for monitoring the nitrate concentration blank measurement data. Furthermore, they used the process capability indices to evaluate the environmental performance of the nitrate blank process to avoid associated risks. Pan and Chen [23] designed an economic CUSUM scheme based on Duncan's model and compared its performance with that of the $\overline{X}$ scheme for monitoring liquid (zinc) waste and industrial pollutants discharged into a river. Leiva et al. [28] designed an attribute control chart for monitoring environmental risks due to dangerous pollutants present in the air, and the performance of the proposed methodology was investigated via simulation study. Similar to [28], Marchant et al. [29] proposed a methodology for monitoring particulate matter pollutants present in the environment using bivariate SPM charts. Capezza et al. [30] discussed traditional multivariate techniques for monitoring the total CO_2 emissions from a cruise ship, on different voyages, to detect anomalous occurrences.

The abovementioned SPM schemes are designed for monitoring either a single value or a few specific values of process shift. However, in almost all real applications, predicting the process shift is extremely cumbersome because the size δ of a shift in the process mean is a random variable that varies from time to time [31]. Consequently, an SPM scheme established considering a single value or a few specific values of δ may not satisfactorily capture the real characteristics of the process effectively. On the contrary, if data on δ are collected, the distribution of δ can be estimated and an optimal SPM scheme can be designed so that its effectiveness can be enhanced over a wide range of δ rather than a specific shift point. In addition, most of the abovementioned models assume that the quality characteristics x to be monitored are normally distributed, which is not always the case in environmental pollution processes. In most of the real applications, the environmental data is non-normal, and thus the traditional SPM schemes cannot be used directly for monitoring them. Liu and Xue [24] proposed a cost-based exponentially weighted moving average (EWMA) scheme (known as ML-EWMA chart) for monitoring the non-normal environmental data, assuming a random shift δ in the environmental pollution process. The proposed model minimizes only the quality loss experienced by an environmental pollution process based on Taguchi's loss function. However, the primary goal of implementing an economic SPM scheme is to minimize the expected total cost, including the cost due to quality loss and operational costs of the SPM scheme. Several extensions to the pioneering economic design of $\overline{X}$ scheme, developed by [32], have been proposed (for instance, see [33–37]). Although the economic design of an SPM scheme is popular, it suffers from poor statistical properties (e.g., high false alarm rate). Therefore, several scholars have developed economic-statistical designs of an SPM scheme to reduce the false alarm rate (for instance, see [36,38–40]).

It is well-known that the traditional $\overline{X}$ scheme is a better choice for detecting large process shifts, whereas the EWMA and CUSUM schemes are mainly used for detecting small process shifts [25]. The effectiveness of the EWMA scheme is comparable to that of the CUSUM scheme; however, the former is easier to design and operate [25]. An SPM scheme combining both $\overline{X}$ and EWMA charts can enhance the performance of the monitoring scheme for detecting both small and large shifts in the environmental pollution processes. This study presents an optimization model for the economic-statistical design of the combined $\overline{X}$& EWMA scheme for monitoring carbon emissions from industrial sectors, considering random shifts in the emission process. The contribution of the proposed study is summarized as follows: (i) the proposed model optimizes the charting parameters including the sample size, sampling interval, weighting parameter, and control limits of the combined $\overline{X}$& EWMA scheme, and, in the meantime, ensures that no extra resources for operating the SPM scheme will be necessary. (ii) The proposed SPM scheme minimizes the expected total cost including the cost due to quality loss in the emission process and the operational cost of the SPM scheme. (iii) The performance of the proposed $\overline{X}$&EWMA scheme is compared to basic $\overline{X}$, EWMA and $\overline{X}$&EWMA schemes. The study shows that the proposed combined $\overline{X}$&EWMA scheme is significantly superior to its competitors for monitoring an environmental process. (iv) The performance of the proposed $\overline{X}$&EWMA scheme is investigated extensively under different operational scenarios to help practitioners identify the optimal charting parameters using a computer program, available upon request. (v) The design and application of the proposed SPM scheme are illustrated by a real case study to promote its practical use.

3. Model development

3.1. Assumptions

Formulating the model proposed in this article involves the following assumptions:

(1) The emission process begins from an in-control (IC) condition. The carbon emission variable x is independent and has normal distribution, with IC mean μ_0 and standard deviation (SD) σ_0. An assignable cause will alter the IC mean μ_0 to out-of-control (OOC) mean μ_1:

$$\mu_1 = \mu_0 + \delta\sigma_0 \tag{1}$$

where δ is the size of the shift in the mean value of the carbon emission process, experienced by an assignable cause, if the emission process is in the IC state, $\delta = 0$. To simplify the process of designing the model, the shift in the SD of the emission process is not considered in this study (i.e., $\sigma \equiv \sigma_0$).

(2) The shift of size δ in the mean value of the carbon emission process is characterized by a Rayleigh distribution. This distribution is well-accepted in the SPM research community as a realistic representative of the distribution of the process shift [41–43].

(3) The OOC state occurs owing to a single assignable cause in the emission process. The incidence of the assignable cause is assumed to follow a homogenous Poisson process, with mean λ_a (i.e., the length of the IC state of the emission process follows an exponential distribution with a mean of $1/\lambda_a$). This is a critical assumption, however, such assumption substantially simplifies the process of designing the economic model [25].

(4) The carbon emission process continues during identifying and fixing the assignable cause.

3.2. Notations

The notations used in this study and their definitions are presented in

Table 1
Notations used in designing the optimization model.

λ	The EWMA weighting factor.
n	Sample size
h	Sampling interval
UCL	Upper control limit of the $\overline{X}$ chart.
H	Upper control limit of the EWMA chart.
μ_0	Mean amount of carbon emissions during the IC state of the emission process.
σ_0	Standard deviation of the amount of carbon emissions during the IC state of the emission process.
USL	Upper specification limit of the amount of carbon emissions.
Q	Amount of carbon emissions per unit time.
λ_a	Incidence rate of the assignable cause.
O	Maximum number of carbon emission data inspected per unit time (i.e., maximum permissible inspection rate).
μ_δ	Mean of the δ values in the carbon emission process.
g	Time required to estimate and test an observed data of a sample of carbon emission.
t_4	Time length from an OOC state to the identification and fixation of the assignable cause.
ζ	Minimum allowable IC ATS_0.
a_1	Fixed part of the sampling cost.
a_2	Variable part of the sampling cost.
a_3	Cost of detecting and dissecting an assignable cause.
a_4	Cost of investigating a false alarm.
C_K	The average penalty cost for an out-of-specification amount of carbon emissions.

Table 1.

Most of the parameters listed in Table 1 can be estimated based on the historical records of the company or factory. The charting parameters (λ, n, h, H, UCL) can be obtained from the optimization algorithm proposed in this research. The process parameters (μ_0, σ_0) can be estimated from the data observed in the pilot runs or process capability studies. The value of the USL can be decided based on the permissible amount of carbon emissions or carbon-cap; the amount of carbon emissions is supposed to not exceed the USL. The value of Q may be estimated from the company's historical records of energy consumption per unit time. The value of the rate of occurrence of assignable cause λ_a can be estimated based on the historical records of OOC cases. The presence of the assignable cause incurs an excessive amount of carbon emissions. An important reason behind the sudden increase in the amount of carbon emissions may be the deterioration of the equipment's efficiency (or operators' negligence) that leads to unnecessary energy consumptions. The root causes of this deterioration may include, but are not limited to, leakages, broken equipment, or worn bearings. The inspection rate O is the time that the company dedicates to running SPM activities—it can be estimated based on the total time that an operator is engaged with the quality of inspection. The value of μ_δ can be estimated based on the sample values of mean shift δ obtained during OOC cases of the emission process [42]. The values of the time components g and t_4 can be easily estimated from a field test. The specification ζ can be decided based on the trade-off between the false alarm rate and the detection power. The value of a_1 can be approximated by considering the cost of the emission metering system (e.g., sensors or other devices) for measuring the amount of energy consumption per unit time. The value of a_2 can be approximated by considering the operational and maintenance costs of the emission metering system and inspectors' salaries. The value of a_3 can be approximated by considering the cost of the equipment used, experts' salaries, and transportation costs. Approximating the cost parameter a_4 is quite similar to a_3, however, a_4 is generally more costly than a_3, as investigating a false alarm is usually longer and needs more sophisticated equipment than detecting and fixing an assignable cause. Finally, the value of C_K can be decided based on the carbon tax.

3.3. Design model

3.3.1. Optimization model

The variables z_i and $\bar{x}_i$ are the two monitoring statistics for the ith sample to be plotted on the combined $\bar{X}$&EWMA scheme, where $\bar{x}_i$ is the mean value of ith sample of carbon emission data collected from different industrial facilities, and z_i is the monitoring statistic of the EWMA scheme that can be calculated as follows:

$$z_i = \lambda\bar{x}_i + (1-\lambda)z_{i-1} \tag{2}$$

where λ ($0 < \lambda < 1$) is the weighting parameter of the EWMA scheme. The initial value of z_i (i.e., at $i = 0$) is the IC mean value of the amount of carbon emissions (i.e., $z_0 = \mu_0$). The combined $\bar{X}$&EWMA scheme will signal an OOC state if the variable z_i falls above the H of the EWMA scheme, and/or the present value of $\bar{x}_i$ exceeds the UCL of the $\bar{X}$ scheme. The OOC state indicates an unusual increase in the amount of carbon emissions owing to an assignable cause, and thus suggests that an initiative must be taken to detect and fix the root causes of that increase. If the plotted points fall below both the UCL and H of the corresponding SPM scheme, the carbon emission process is assumed to be in the IC state, and thus no action is needed.

The optimization model of the $\bar{X}$&EWMA scheme is as follows:

$$\text{Minimize}: \ \text{expected total cost (ETC)}. \tag{3}$$

$$\text{Subject to}: ATS_0 \geq \zeta. \tag{4}$$

$$o \leq O, n \leq n_{max}. \tag{5}$$

Design parameters: λ, n, h, UCL, H.

Here, o represents the resultant inspection rate, and n_{max} is the maximum allowable sample size that the designer wishes to consider. ATS_0 is the maximum allowable in-control average time to signal (or, the false alarm rate) of the SPM scheme. Because the amount of carbon emissions should not exceed the USL, the proposed $\bar{X}$&EWMA scheme is optimized for identifying the increasing shifts in the emission process. Consequently, an upper-sided EWMA scheme and an upper-sided $\bar{X}$ scheme have been combined. The aforementioned model optimizes λ, n, h, UCL, and H to minimize ETC—that is, the expected total cost per unit time owing to carbon emissions during an operational cycle—and, in the meantime, ensures that the constraints on o, n, and ATS_0 are all satisfied.

Amongst all design variables (λ, n, h, UCL, and H), only n and λ are independent. The value of h is determined such that the constraint on o is satisfied:

$$h = n/O. \tag{6}$$

UCL and H are determined such that the constraint on IC ATS_0 (constraint (4)) is satisfied. The objective function ETC is calculated as follows:

$$ETC = \int_0^\infty [TC(\delta) \cdot f_\delta(\delta)]d\delta \tag{7}$$

where $TC(\delta)$ is the total cost incurred owing to carbon emissions per unit time of an operational cycle for a given shift of size δ in the carbon emission process. The calculations of $TC(\delta)$ are explained in the following sections. The probability density function $f(\delta)$ in Eq. (7) is obtained from Rayleigh distribution, as expressed below:

$$f_\delta(\delta) = \frac{\pi\delta}{2\mu_\delta^2}\exp\left(-\frac{\pi\delta^2}{4\mu_\delta^2}\right) \tag{8}$$

It is clear that the probability density function $f(\delta)$ of the Rayleigh distribution is modeled by a single variable—the mean value μ_δ of δ. It can be noted that the data on δ can be obtained through a three-phase statistical process control (SPC) scenario, as suggested by [42].

3.3.2. Estimation of the total cost, TC(δ)

For any given shift of size δ in the emission process, the total cost per unit time of an operational cycle, $TC(\delta)$, is calculated from the ratio of expected cost, $EC(\delta)$, to the expected length, $EL(\delta)$, of the operational cycle.

3.3.2.1. Estimation of the expected length EL(δ) of an operational cycle.

The time length L of an operational cycle is the time period from the beginning (or restoration) of the emission process to the identification and fixation of an assignable cause. This L comprises four time components: the IC time period (t_1), the OOC time period (t_2), the amount of time spent in taking a sample (size n) of carbon emission data and analyzing it (t_3), and the time length from an OOC state to the identification and fixation of an assignable cause (t_4). These four time components are random variables and only their expected values can be obtained.

As indicated earlier, the time between incidences of the assignable causes is assumed to be an exponential distribution with incidence rate λ_a; therefore, the mean time between incidences of the assignable causes (i.e., mean time length of an IC state) is as follows:

$$t_1 = 1/\lambda_a \tag{9}$$

If an assignable cause occurs between two consecutive samples, then the time component t_2 can be estimated as follows [25,32]:

$$t_2 = ATS_1(\delta) - \tau = ATS_1(\delta) - \left(\frac{h}{2} - \frac{\lambda_a h^2}{12}\right) \tag{10}$$

where τ is the expected time of incidence of the process shift (of size δ) between the jth and $(j+1)$th sample, given that the shift occurs during this interval. The expected value of the time period t_3 can be estimated in a straightforward manner, based on n and g.

$$t_3 = g \cdot n \tag{11}$$

Finally, the time period from an OOC state (owing to a process shift of size δ) to the identification and fixation of an assignable cause t_4 can be approximated, based on the historical records of OOC cases.

The expected time length, $EL(\delta)$, can now be calculated based on the time components t_1, t_2, t_3, and t_4.

$$EL(\delta) = t_1 + t_2 + t_3 + t_4 = \frac{1}{\lambda_a} + ATS_1(\delta) - \left(\frac{h}{2} - \frac{\lambda_a h^2}{12}\right) + gn + t_4 \tag{12}$$

3.3.2.2. Estimation of the expected cost EC(δ) of an operational cycle. The primary goal of employing SPM tools is to optimize (i.e., minimize) the *ETC* that includes the quality cost (i.e., cost incurred owing to carbon emissions) and the operational cost of the SPM scheme. The quality cost in an operational cycle (C_1) can be estimated by utilizing the quadratic loss function [44]. The operational cost of the SPM scheme, such as the cost of sampling and estimating carbon emission data (C_2), cost of examining a false alarm (C_3), and cost of detecting and dissecting an assignable cause (a_3) in an operational cycle, can be estimated on the basis of the cost parameters, specified in the model developed by [32].

The quality cost C_1, defined as the cost incurred owing to a shift of size δ in the carbon emission process, can be estimated on the basis of Taguchi's loss function concept [44].

$$\begin{aligned} C_1 &= \left[EL(\delta) - \frac{1}{\lambda_a}\right] \cdot Q \cdot K \cdot \left(\sigma_0^2 + \delta^2 \sigma_0^2\right) \\ K &= \frac{C_K}{(USL - \mu_0)^2} \end{aligned} \tag{13}$$

Here, $1/\lambda_a$ is the time length of the IC period, $[EL(\delta) - 1/\lambda_a]$ is the time length of the OOC period owing to a shift of size δ, and K is the cost coefficient, estimated based on the cost component C_K associated with the *USL* (carbon-cap).

The expected cost of sampling and estimating the carbon emission data, C_2, can be estimated based on the fixed (a_1) and variable (a_2) sampling cost components.

$$C_2 = \frac{(a_1 + a_2 n) \cdot EL(\delta)}{h} \tag{14}$$

The expected cost of investigating a false alarm in an operational cycle, C_3, can be determined based on the time length of the IC period $1/\lambda_a$, the IC ATS_0, and the cost of examining a false alarm, a_4.

$$C_3 = \frac{a_4}{\lambda_a \cdot ATS_0} \tag{15}$$

Thus, the expected cost incurred owing to a shift of size δ in the emission process in an operation cycle, $EC(\delta)$, can be obtained by adding all the cost components, C_1, C_2, C_3, and a_3.

$$\begin{aligned} EC(\delta) &= C_1 + C_2 + C_3 + a_3 \\ &= \left[EL(\delta) - \frac{1}{\lambda_a}\right] \cdot Q \cdot K \cdot \left(\sigma_0^2 + \delta^2 \sigma_0^2\right) + \frac{(a_1 + a_2 n) \cdot EL(\delta)}{h} + \frac{a_4}{\lambda_a \cdot ATS_0} + a_3 \end{aligned} \tag{16}$$

Finally, the total cost incurred owing to carbon emissions, per unit time of an operational cycle, for any given value of δ, $TC(\delta)$, can be found as follows:

$$TC(\delta) = \frac{EC(\delta)}{EL(\delta)} \tag{17}$$

In summary, for any given set of values of the process parameters (λ_a, O, μ_δ, g, t_4, ζ, USL, Q, μ_0, and σ_0), cost parameters (a_1, a_2, a_3, a_4, and C_K), and design parameters (λ, n, h, UCL, and H), the $TC(\delta)$ can be calculated as follows:

(1) Estimate the expected length of an operational cycle.
  1.1. Calculate t_1 using Eq. (9).
  1.2. Calculate t_2 using Eq. (10), in which ATS_1 for any given value of shift of size δ in the carbon emission process is calculated by a Markov chain approach [45].
  1.3. Calculate t_3 using Eq. (11).
  1.4. Calculate $EL(\delta)$ using Eq. (12).
(2) Estimate the expected cost of an operational cycle.
  2.1. For a given value of δ, calculate C_1 using Eq. (13).
  2.2. Calculate C_2 using Eq. (14).
  2.3. Calculate C_3 using Eq. (15), in which ATS_0 is calculated ($\delta = 0$) by a Markov chain approach [45].
  2.4. Calculate $EC(\delta)$ using Eq. (16).
(3) Calculate $TC(\delta)$ using Eq. (17).

3.3.3. Optimization process

Fig. 1 illustrates the process of optimization design of the proposed economic-statistical $\overline{X}$&EWMA scheme.

The optimization process is terminated if no further improvement in the *ETC* value is found. At the end of optimization process, the combination of the optimal design parameters (λ, n, h, UCL, and H) that ensures the minimum *ETC* and satisfies the constraints ($o \le O$), ($n \le n_{max}$), and ($ATS_0 \ge \tau$), is identified. Because the design is optimized under the standard condition ($\mu_0 = 0$, $\sigma_0 = 1$), the actual control limits are calculated using the actual values of μ_0 and σ_0.

$$\begin{aligned} UCL_{actual} &= \mu_0 + \sigma_0 \cdot UCL \\ H_{actual} &= \mu_0 + \sigma_0 \cdot H \end{aligned} \tag{18}$$

A computer program using C language was developed to automate the design process of the optimal economic-statistical $\overline{X}$*&EWMA* scheme. The program is available upon request.

4. Numerical studies

4.1. Comparison study

The effectiveness of four SPM schemes is compared in this section:

(1) The basic economic-statistical $\overline{X}$ scheme: This is a conventional economic-statistical $\overline{X}$ scheme that uses a sample size of five ($n = 5$). An $\overline{X}$ scheme is usually designed by considering a constant sample size of five [25].
(2) The basic economic-statistical EWMA scheme: This EWMA scheme is designed by assuming a constant weighting parameter, λ, of 0.1 and a constant sample size, n, of 1. The value of parameter λ is subjectively selected from the widely used values of 0.05, 0.1, or 0.20 [25], and an EWMA scheme with $n = 1$ is known to be successful from an overall perspective [31].
(3) The basic economic-statistical $\overline{X}$*&EWMA* scheme: Similar to the basic economic-statistical EWMA scheme, this $\overline{X}$*&EWMA* combination uses λ value of 0.1 and n value of 1. Following [46], the value of *UCL* of the $\overline{X}$ scheme is set at 4.25, while the parameter H of the EWMA scheme is decided to ensure that the constraint of ($ATS_0 \ge \zeta$) is satisfied.
(4) The optimal economic-statistical $\overline{X}$*&EWMA* scheme: The values of the design parameters (n, h, λ, UCL, and H) of this scheme are optimized by following the algorithm illustrated in Fig. 1.

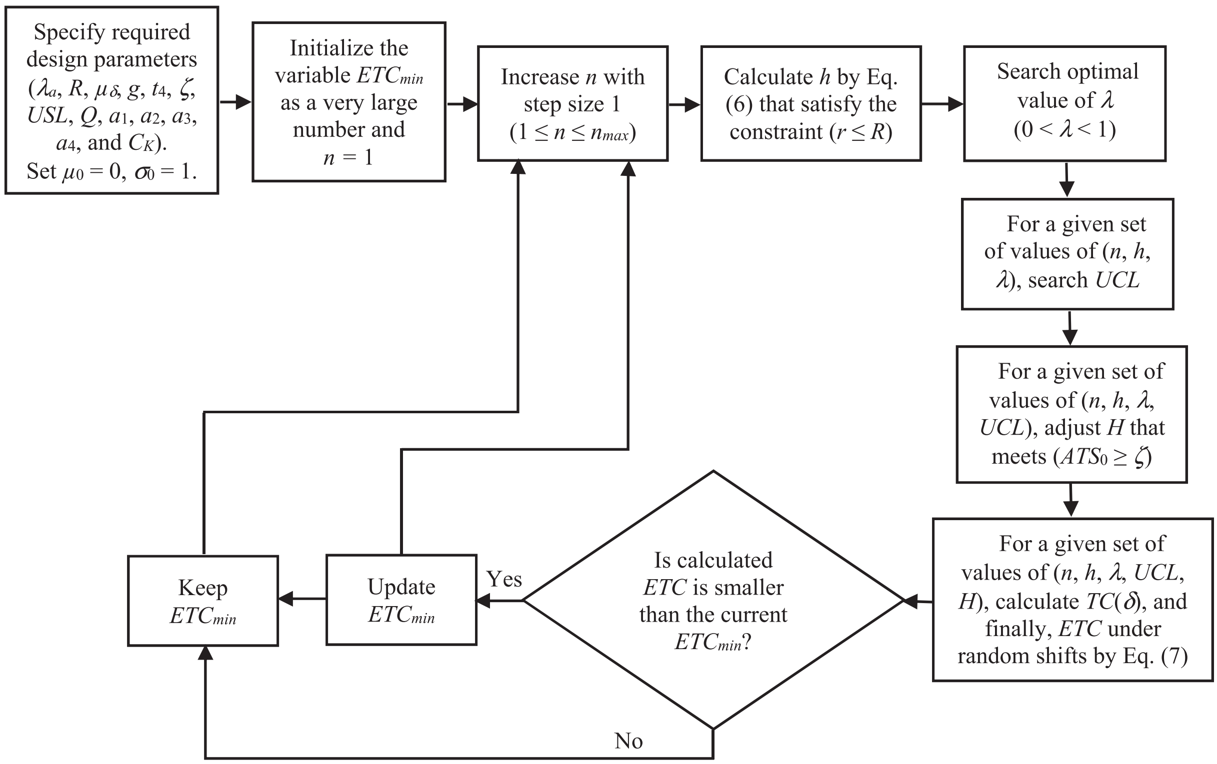


Fig. 1. Optimization algorithm of the proposed economic-statistical $\overline{X}$&EWMA scheme.

To facilitate the comparison, a normalized ETC_{normal} value for each SPM scheme is calculated as follows:

$$ETC_{normal} = \frac{ETC}{ETC_{opt}} \tag{19}$$

where ETC and ETC_{opt} are the expected total costs of a specific SPM scheme and the optimal $\overline{X}$&*EWMA* scheme, respectively. An ETC_{normal} value greater than 1 of a scheme indicates that its effectiveness is poorer than that of the optimal economic-statistical $\overline{X}$&*EWMA* scheme, and vice versa. The four SPM schemes are designed under the standard condition ($\mu_0 = 0$, $\sigma_0 = 1$), and n_{max} is assumed to be fixed at 15 in this study, as handling a large sample size is not preferable in practice.

Because of the large number of input variables (eight process parameters [λ_a, O, μ_δ, g, t_4, ζ, USL, and Q] and five cost parameters [a_1, a_2, a_3, a_4, and C_K]), the effectiveness of the four SPM schemes is investigated using a 2_{IV}^{13-8} fractional factorial design [25]. The 13 input variables are considered as the factors, and ETC_{normal} (Eq. (19)) is considered the response. Each of the 13 factors vary at two levels, as displayed in Table 2.

For each of the 32 runs resulting from the 2_{IV}^{13-8} factorial design, the four SPM schemes are designed in such a way that each of them ensures the satisfaction of all constraints. The resultant ETC_{normal} values (see Table 3) showed that the developed optimal economic-statistical $\overline{X}$&*EWMA* scheme consistently outperformed the other schemes throughout the 32 runs.

The average of the ETC_{normal} values, $\overline{ETC}_{normal}$, over the 32 runs for each scheme, was also calculated. The values of $\overline{ETC}_{normal}$ showed that from a general viewpoint (over different combinations of λ_a, O, μ_δ, g, t_4, ζ, USL, Q, a_1, a_2, a_3, a_4, and C_K), the optimal economic-statistical $\overline{X}$&EWMA scheme outperformed (in terms of ETC) the basic economic-statistical $\overline{X}$, basic economic-statistical EWMA, and basic economic-statistical $\overline{X}$&EWMA schemes by about 40%, 77%, and 28%, respectively. The improvement in the effectiveness of the optimal economic-statistical $\overline{X}$&*EWMA* scheme compared with that of the other three schemes was further investigated using paired t-tests [25] (see bottom row of Table 3). The results showed that the improvements in the effectiveness of the optimal economic-statistical $\overline{X}$&*EWMA* scheme compared with the basic economic-statistical $\overline{X}$ scheme (p-value $=$ 0.004), basic economic-statistical EWMA scheme (p-value $=$ 0.010), and basic economic-statistical $\overline{X}$&*EWMA* scheme (p-value $=$ 0.012) were all statistically significant, using a significance level of 5%.

Table 2
Factors levels.

Input factor	Low level	High level
λ_a: Rate of occurrence of the assignable cause (occurrences per month)	0.5	1.0
O: Maximum allowable inspection rate (number of data inspected per month)	2	5
μ_δ: Mean of the mean shifts δ in the amount of carbon emission process	0.5	3.5
g: Time to estimate and test an observed data of a sample of carbon emission (month)	0.001388	0.006944
t_4: Time period from the detection of the lack of control to the location and removable of the assignable cause (month)	0.034	0.10
ζ: Minimum allowable in-control ATS_0 (month)	300	800
USL: Upper specification limit (i.e. carbon-cap) of the amount of carbon emission (tons per month)	$3\sigma_0$	$6\sigma_0$
Q: Amount of carbon emission (tons per month)	5,000,000	70,000,000
a_1: Fixed component of sampling cost ($)	200	500
a_2: Variable component of sampling cost ($)	20	50
a_3: Cost of finding and fixing an assignable cause ($)	500	1000
a_4: Cost of examining a false alarm ($)	1000	2000
C_K: Average penalty cost for an out-of-specification amount of carbon emission ($ per ton)	100	200

4.2. Sensitivity analysis

The impacts of the 13 input variables (λ_a, O, μ_δ, g, t_4, ζ, USL, Q, a_1, a_2, a_3, a_4, and C_K) on the response parameter (ETC) of the optimal

Table 3
Comparison of the four schemes in the 2_{IV}^{13-8} experiment.

Run	Values of the input factors													ETC_{normal}		
	λ_a	O	μ_d	g	t_4	ζ	USL	Q	a_1	a_2	a_3	a_4	C_K	Basic economic $\overline{X}$ scheme	Basic economic EWMA scheme	Basic economic $\overline{X}$&EWMA scheme
1	1.0	2	0.5	0.001388	0.034	800	3	70,000,000	200	50	1000	2000	200	1.044183	1.012824	1.018393
2	1.0	5	3.5	0.006944	0.1	800	6	70,000,000	500	50	1000	2000	200	1.281763	1.944134	1.271647
3	1.0	5	3.5	0.006944	0.034	300	3	70,000,000	200	20	500	2000	100	1.590400	2.526476	1.489510
4	0.5	2	0.5	0.006944	0.1	800	6	5,000,000	200	20	1000	2000	100	1.108547	1.048648	1.060258
5	1.0	2	0.5	0.001388	0.1	300	6	70,000,000	500	20	500	2000	100	1.041737	1.019280	1.023371
6	0.5	5	3.5	0.006944	0.034	800	3	5,000,000	200	50	1000	1000	200	1.230401	2.919129	1.609679
7	0.5	5	0.5	0.006944	0.1	800	3	70,000,000	200	50	500	2000	100	1.253467	1.098450	1.133177
8	1.0	5	0.5	0.001388	0.1	300	3	5,000,000	500	50	1000	2000	100	1.142403	1.070108	1.084509
9	0.5	2	3.5	0.006944	0.034	800	6	70,000,000	200	20	500	1000	200	1.889407	3.095460	1.680539
10	1.0	2	3.5	0.006944	0.1	800	3	5,000,000	500	20	500	2000	200	1.929168	1.982431	1.250452
11	1.0	2	0.5	0.006944	0.034	800	3	70,000,000	500	20	1000	1000	100	1.043687	1.012236	1.017800
12	0.5	2	3.5	0.001388	0.034	800	6	70,000,000	500	50	500	2000	100	1.874926	3.269105	1.758212
13	0.5	2	3.5	0.001388	0.1	300	3	70,000,000	200	20	1000	2000	200	1.716298	2.402608	1.528584
14	1.0	5	0.5	0.006944	0.034	800	6	5,000,000	500	50	500	1000	100	1.132989	1.049958	1.067793
15	0.5	2	3.5	0.006944	0.1	300	3	70,000,000	500	50	1000	1000	100	1.734309	2.309441	1.479258
16	1.0	5	0.5	0.001388	0.034	800	6	5,000,000	200	20	500	2000	200	1.138132	1.054799	1.072739
17	1.0	5	3.5	0.001388	0.1	800	6	70,000,000	200	20	1000	1000	100	1.223968	2.037341	1.319367
18	0.5	5	0.5	0.006944	0.034	300	6	70,000,000	500	20	1000	2000	200	1.280794	1.137664	1.167537
19	0.5	2	0.5	0.001388	0.034	300	3	5,000,000	200	20	500	1000	100	1.113493	1.070860	1.079974
20	1.0	2	3.5	0.001388	0.034	300	6	5,000,000	500	20	1000	1000	200	2.537016	2.323587	1.396564
21	0.5	2	0.5	0.001388	0.1	800	6	5,000,000	500	50	1000	1000	200	1.110599	1.050772	1.062411
22	1.0	5	0.5	0.006944	0.1	300	3	5,000,000	200	20	1000	1000	200	1.135590	1.063194	1.077486
23	1.0	2	0.5	0.006944	0.1	300	6	70,000,000	200	50	500	1000	200	1.041106	1.018390	1.022477
24	0.5	2	0.5	0.006944	0.034	300	3	5,000,000	500	50	500	2000	200	1.110701	1.067715	1.076799
25	1.0	2	3.5	0.001388	0.1	800	3	5,000,000	200	50	500	1000	100	1.947692	2.042654	1.278868
26	1.0	5	3.5	0.001388	0.034	300	3	70,000,000	500	50	500	1000	200	1.514647	2.780972	1.611236
27	1.0	2	3.5	0.006944	0.034	300	6	5,000,000	200	50	1000	2000	100	2.539370	2.275298	1.381982
28	0.5	5	3.5	0.006944	0.1	300	6	5,000,000	500	20	500	1000	100	1.161919	2.032520	1.353036
29	0.5	5	0.5	0.001388	0.034	300	6	70,000,000	200	50	1000	1000	100	1.293614	1.149750	1.179980
30	0.5	5	3.5	0.001388	0.034	800	3	5,000,000	500	20	1000	2000	100	1.160881	3.377457	1.834085
31	0.5	5	3.5	0.001388	0.1	300	6	5,000,000	200	50	500	2000	200	1.113594	2.214082	1.460564
32	0.5	5	0.5	0.001388	0.1	800	3	70,000,000	500	20	500	1000	200	1.261915	1.106091	1.141100
$\overline{ETC}_{normal}$														1.4011871	1.7889465	1.285428613
Δ^a p-value														+2106914660.004	+4555877360.010	+1590885800.012

[a] $\Delta = \overline{ETC}$ of a chart over 32 runs - $\overline{ETC}$ of the optimal $\overline{X}$&EWMA scheme over 32 runs. Positive values indicate superiority of optimal $\overline{X}$&EWMA scheme to other schemes.

economic-statistical $\overline{X}$&*EWMA* scheme were also investigated using the 2_{IV}^{13-8} factorial design indicated in Table 2. Because the replication size was 1, the higher order (higher than or equal to the third order) interaction effects were combined to estimate the sum of squares of the error. The significant main and two-factor interaction effects were identified by an analysis of variance (ANOVA). Before performing the ANOVA test, a normality test of the *ETC* data was performed to check the model adequacy. The data on *ETC* were initially not normal; therefore, Johnson transformation was conducted before performing the ANOVA test (see Fig. 2).

The results of the ANOVA test, as shown in Table 4, confirm that only four main factor effects (bold text) were statistically significant.

As shown in Table 4, the *ETC* of the optimal economic-statistical $\overline{X}$&*EWMA* scheme is positively affected by μ_δ (*p*-value = 0.028), *Q* (*p*-value = 0.001), and C_K (*p*-value = 0.010). This implies that a larger μ_δ (or *Q* or C_K) value can result in a larger *ETC*, and vice versa. Conversely, the *ETC* is negatively affected by *USL* (*p*-value = 0.002). This means a tighter *USL* (carbon-cap) can result in a larger *ETC*, and vice versa. This is justifiable as a smaller *USL* needs to utilize more resources and more investigations.

Table 4
Factor effects in the ANOVA test.

Input factors	Effects on the *ETC* of the optimal $\overline{X}$&EWMA scheme	
	Effect	p-value
λ_a	0.2006	0.134
O	−0.2463	0.087
$\boldsymbol{\mu_d}$	**0.3916**	**0.028**
g	−0.1746	0.174
t_4	0.1384	0.254
ζ	−0.1001	0.383
USL	**−0.9402**	**0.002**
Q	**1.5091**	**0.001**
a_1	−0.0577	0.598
a_2	−0.0410	0.705
a_3	0.0704	0.526
a_4	0.0933	0.413
$\boldsymbol{C_K}$	**0.5796**	**0.010**
λ_a*R	0.0162	0.880
λ_a*μd	0.1033	0.370
λ_a*g	0.0737	0.508
λ_a*t4	−0.0220	0.837
λ_a*z	0.1556	0.211
λ_a*USL	0.0480	0.659
λ_a*Q	−0.1500	0.224
λ_a*a_1	0.0516	0.636
λ_a*a_2	0.0129	0.904
λ_a*a_3	−0.0208	0.846
λ_a*a_4	0.0189	0.860
λ_a*C_K	−0.0370	0.731
R*g	0.0379	0.725
R*a_4	−0.0599	0.585
R*C_K	−0.0609	0.579

5. Case study

The design and application of the optimal economic-statistical $\overline{X}$&*EWMA* scheme are demonstrated based on real data on the amount of carbon emissions from factories in the United States and are explained in the following steps.

5.1. Data collection

In 2017, the estimated GHGs emissions from the industrial sector represented 22.2% of the total emissions of GHGs in the United States [47]. Manufacturing and industrial processes together produce large amounts of GHGs, specifically CO_2. The State Department of Environmental Conservation (DEC) of New York, as part of its mission to conserve natural resources and protect the environment, keeps records of different sources of pollution, including industrial facilities that emit or have the potential to emit air pollutants, requiring these facilities to

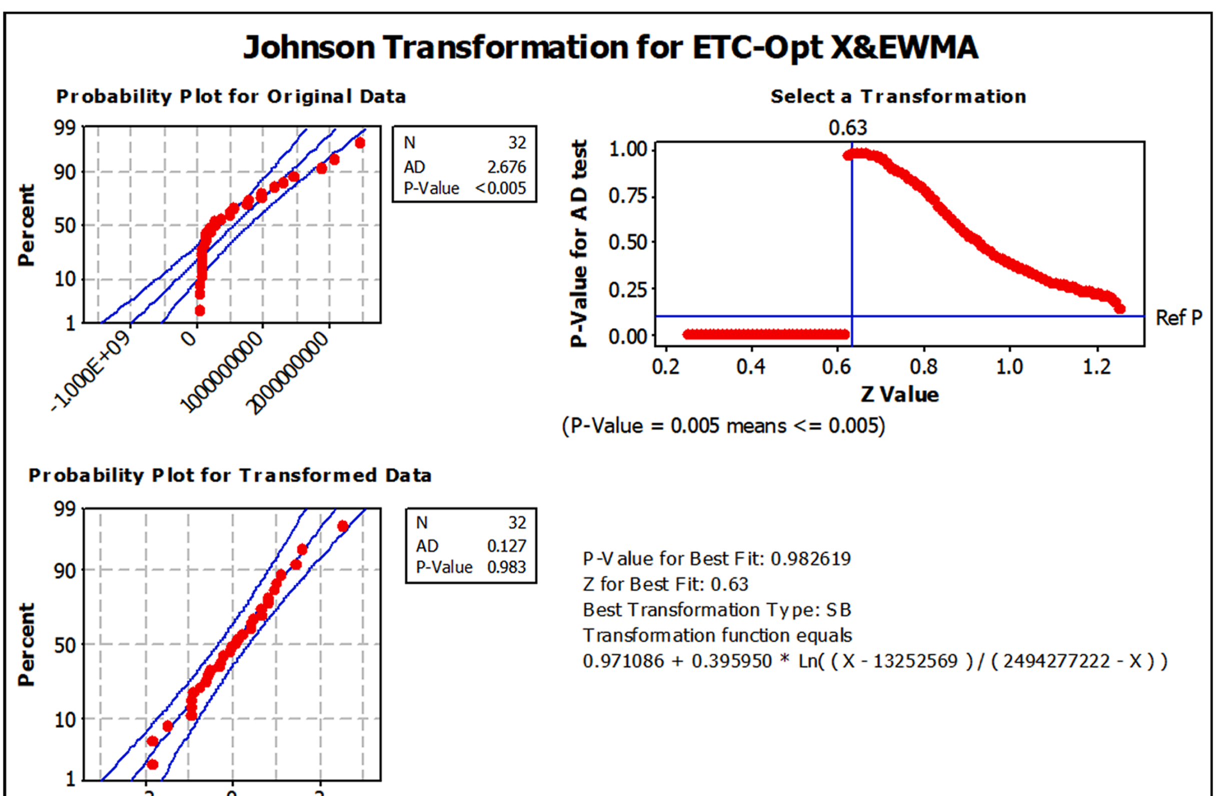


Fig. 2. Normality check of the *ETC* data of the optimal economic-statistical $\overline{X}$&*EWMA* scheme.

report their emissions of pollutants. These reports are public information and can be obtained from the permitting authority [48]. The DEC monitors these industrial facilities to ensure that the source complies with the emission limit, or other pollution control requirements. The SPM charts would be appropriate to achieve this objective.

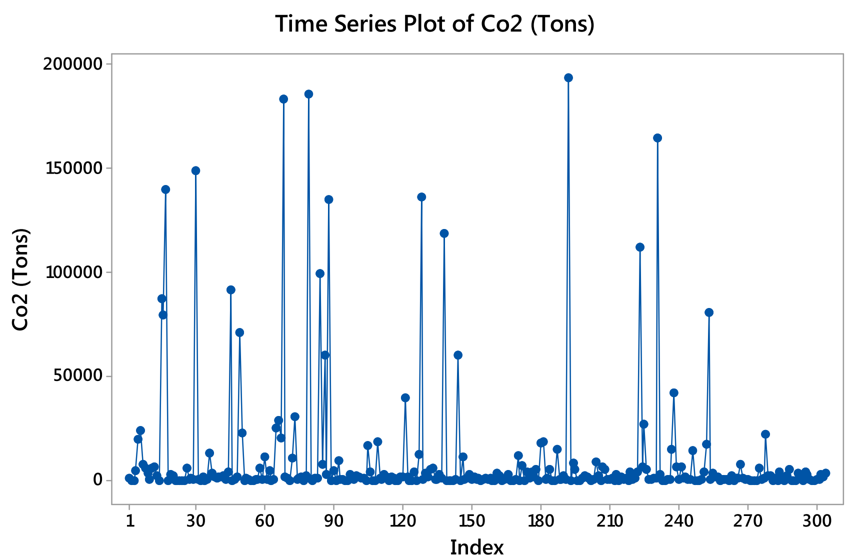
A dataset of the annual CO_2 emissions measured in tons for 306 facilities at 53 different counties in the New York State in 2011 [49], collected by the State DEC, has been utilized in this study. Based on the annual data obtained, the monthly CO_2 emissions data have been calculated and used for illustrating the concept of SPM schemes for monitoring carbon emissions and controlling air quality.

5.2. Model adequacy test

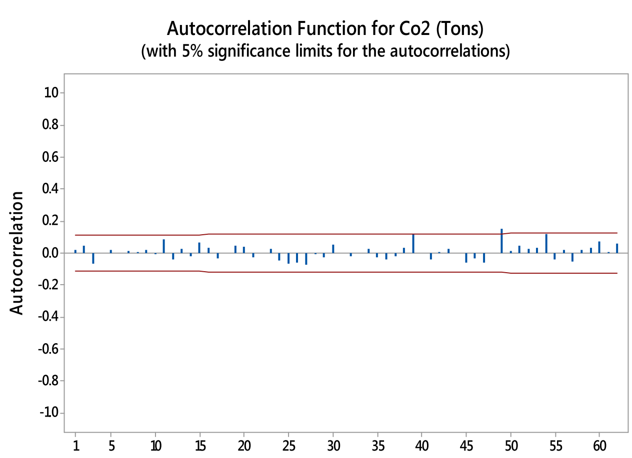
In designing an SPM scheme for variable-type quality characteristics, the quality characteristic x (data on the amount of carbon emissions in this study) is presumed to be normally and independently distributed. A slight or moderate degree of violation of the normality assumption may not affect the effectiveness of an SPM scheme. However, a slight dependency (autocorrelation) among the data significantly affects the effectiveness of an SPM scheme, and thus the dependency of the data should be checked before designing. To verify the assumption of independency, a time series plot was used to represent the carbon emissions data as in Fig. 3(a), which does not show any evidence of seasonality in the data. In addition, autocorrelation function (ACF) and partial ACF (PACF) were also drawn to explore how the data points are related to each other (see Fig. 3(b-c)). Fig. 3(a-c) confirms that the emission data are independent. However, according to the normal probability plot shown in Fig. 4(a), the data are not normally distributed (p-value < 0.01). Thus, a transformation technique is required to transform the non-normally distributed data into normally distributed data [50]. The ordered quantile (ORQ) normalization technique was used for this purpose, achieved using the package "bestNormalize" (version 1.4.2) available in *R* programming language (version 3.6.2). The transformed data satisfied the normality assumption (p-value $>$ 0.15), as illustrated in Fig. 4(b). Finally, the concept of SPM schemes for monitoring carbon emissions was demonstrated based on the transformed data that satisfied both the normality and independency assumptions.

5.3. Design and application of the proposed SPM scheme

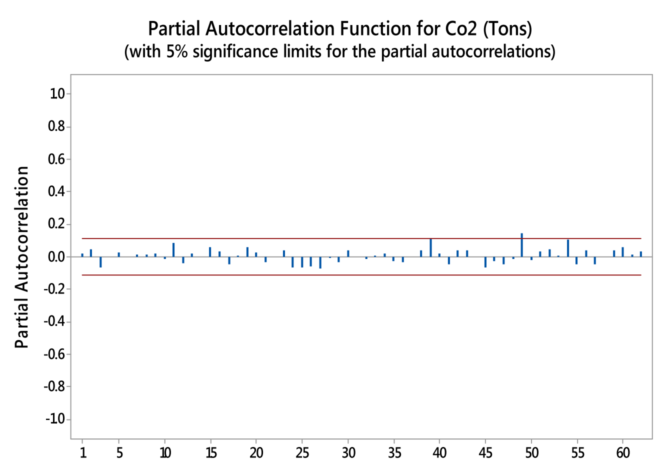
The design of an SPM scheme is accomplished in two phases: Phase I and Phase II operations. In Phase I operation, at least 25–30 samples,



(a) Time series plot

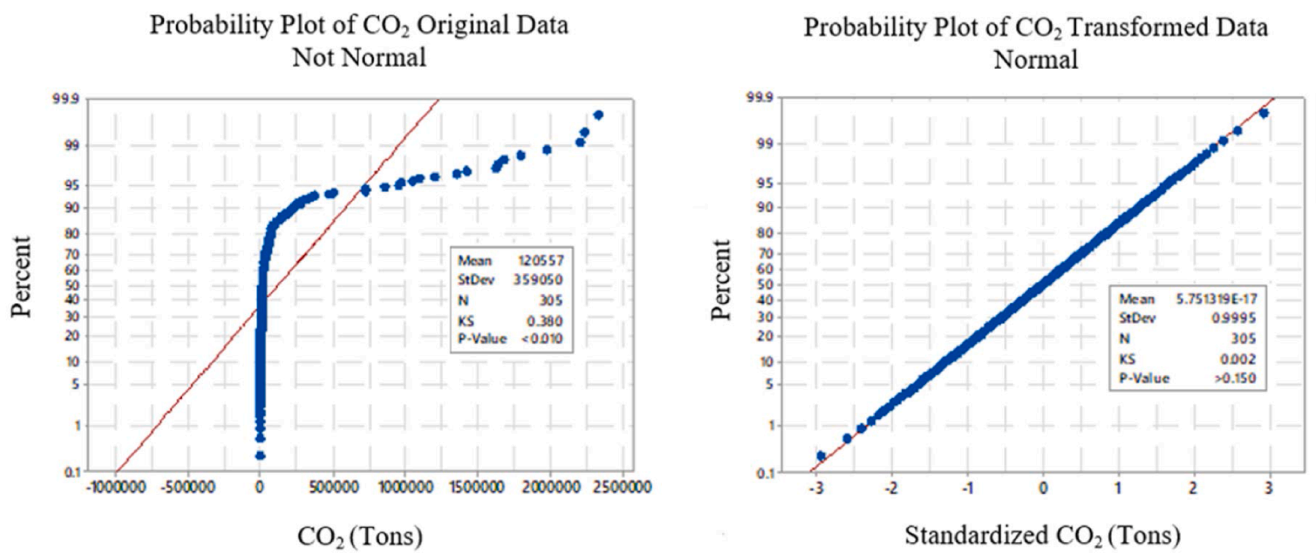


(b) Autocorrelation function



(c) Partial autocorrelation function

Fig. 3. Independency check of the carbon emission data.



(a) Normality check of original CO_2 data (b) Normality check of transformed CO_2 data

Fig. 4. Normality check of the carbon emission data.

each of size five, are usually recommended in designing a classical $\overline{X}$ scheme [25]. The objective of collecting samples in Phase I is to estimate the IC values of μ_0 and σ_0 for designing the SPM scheme. In Phase II, the SPM scheme designed at the end of Phase I is utilized for monitoring the process in the future.

5.3.1. Phase I operation

After the initial screening, 295 observations (59 samples with sample size of five) of carbon emissions data were used in Phase I for designing the basic $\overline{X}\&R$ scheme. Fig. 5 shows phase I SPM scheme. Designing both the $\overline{X}$ scheme (for monitoring the process mean) and R scheme (for monitoring the process dispersion) is recommended in Phase I to ensure that no assignable cause is presented in the process (i.e., the process is in the IC state), and that the estimated μ_0 and σ_0 that will be used in Phase II are consistent [25].

Fig. 5 shows that all the 59 sample points are plotted within the control limits ($\overline{X}$ scheme: $UCL = 1.357$, $CL = 0.015$, $LCL = -1.327$; R scheme: $UCL = 4.918$, $CL = 2.326$, $LCL = 0$) of the $\overline{X}\&R$ scheme, indicating that the carbon emission process is in IC state ($\mu_0 = 0.015$ and $\sigma_0 = 0.9995$).

5.3.2. Phase II operation

The process parameters in the IC state ($\mu_0 = 0.015$, $\sigma_0 = 0.9995$),

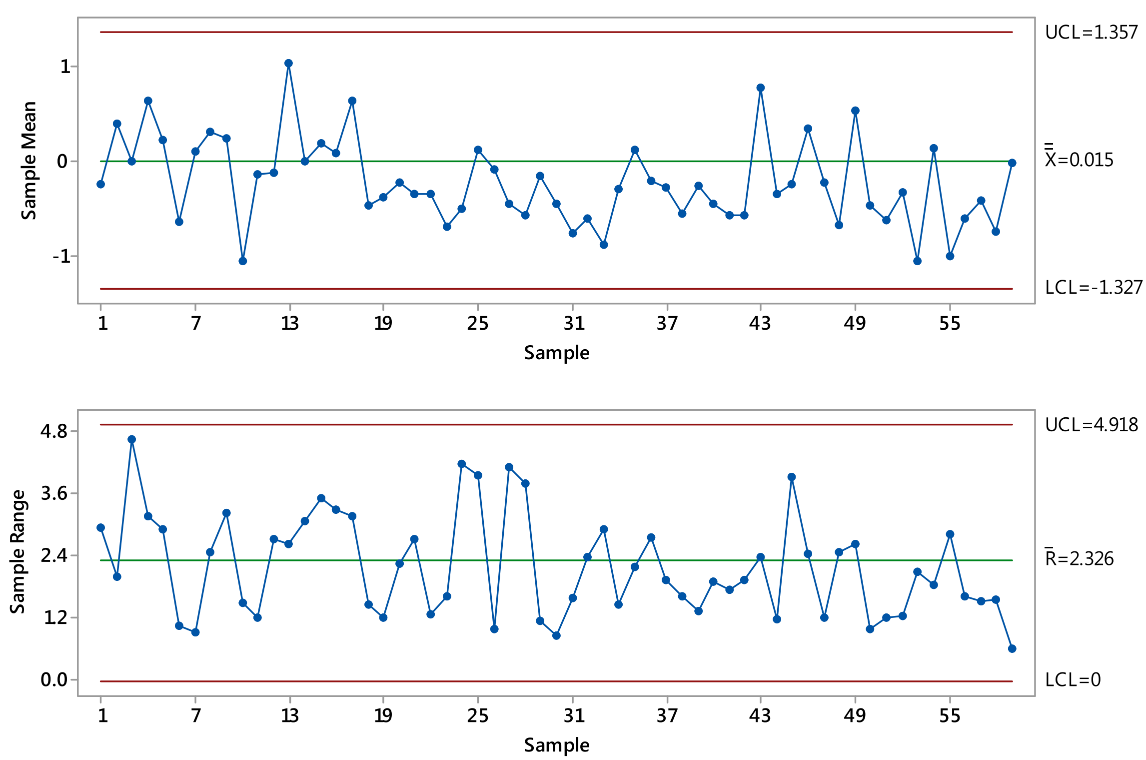


Fig. 5. $\overline{X}\&R$ scheme for carbon emission data in Phase I.

estimated in Phase I, were used in this phase to design a basic economic-statistical $\overline{X}$ scheme, a basic economic-statistical EWMA scheme, a basic economic-statistical $\overline{X}$&EWMA scheme, and an optimal economic-statistical $\overline{X}$&EWMA scheme for monitoring the forthcoming data on the amount of carbon emissions. To design and demonstrate the effectiveness of the proposed SPM schemes, the other required design parameter values assumed are as follows:

- λ_a (occurrence rate of the assignable cause, occurrences per month) $= 0.01$
- (maximum allowable inspection rate (per month)) = 5
- μ_δ (mean of the δ values in the emission process) $= 0.75$
- g (time to estimate and test the observed data of a sample of carbon emissions, month) $= 0.00035$
- t_4 (time period from the detection of an OOC state to the identification and fixation of the assignable cause, month) $= 0.1$
- ζ (minimum allowable IC ATS_0, month) $= 400$
- USL (upper specification limit (carbon-cap) of the amount of carbon emissions, tons per month) $= 4\sigma_0$
- Q (average amount of carbon emissions from an industry, tons per month) $= 12500$
- a_1 (fixed part of the sampling cost, \$) $= 0.5$
- a_2 (variable part of the sampling cost, \$) $= 0.1$
- a_3 (cost of identifying and fixing an assignable cause, \$) $= 100$
- a_4 (cost of investigating a false alarm, \$) $= 200$
- C_K (average penalty cost for an out-of-specification [out-of-carbon cap] amount of carbon emissions, \$ per ton of CO_2 emissions) $= 150$

The abovementioned hypothetical data have been used in this study to illustrate the effectiveness of the proposed SPM schemes. However, the value of the penalty cost C_K was set at $150/ton, according to the current carbon tax in Sweden [51]. In addition, real data for other parameters can be used when the data are publicly accessible. In this example, the maximum allowable sample size n_{max} is considered 10. The developed computer program used to design the four SPM schemes and the parameter values of each scheme are listed below. Note that the designs of all SPM schemes ensure that all constraints (4) and (5) in Section 3 are satisfied.

- Basic economic-statistical $\overline{X}$ scheme:

$n = 5$, $h = 1.0$, $UCL = 1.2697$, $ETC = 20817.98$, $ETC_{normal} = 2.607$

- Basic economic-statistical EWMA scheme:

$n = 1$, $h = 0.20$, $\lambda = 0.10$, $H = 0.7539$, $ETC = 12862.38$, $ETC_{normal} = 1.610$

- Basic economic-statistical $\overline{X}$&EWMA scheme:

$n = 1, h = 2.0, \lambda = 0.10, UCL = 4.2629, H = 0.7552, ETC = 12919.80,$ $ETC_{normal} = 1.618$

- Optimal economic-statistical $\overline{X}$&EWMA scheme:

$n = 10, h = 2.0, \lambda = 0.17, UCL = 1.1725, H = 0.2559, ETC = 7986.75,$ $ETC_{normal} = 1.000$

Because of the unavailability of the real data on OOC states, the effectiveness of the four designed SPM schemes for detecting an OOC signal was investigated via simulation study, in which 20 sample data on the amount of carbon emissions were generated. The first 10 sample data were simulated under the IC condition, and the other 10 considering a 1.0σ shift in the mean of the carbon emission process (i.e., under the OOC condition). It is a common practice in the literature to use simulation to study the effectiveness of a proposed model when real data are unavailable (for instance, see [28,29,52]. All the 20 simulated data are plotted on the four SPM schemes, as shown in Fig. 6.

As shown in Fig. 6(a-d), all three basic SPM schemes ($\overline{X}$, EWMA, and $\overline{X}$&EWMA schemes) were unable to identify the OOC condition of the process. However, the proposed optimal $\overline{X}$&EWMA scheme identified the OOC condition by the 13th sample, evidently demonstrating its supremacy over the basic SPM counterparts. The improvement in the detection effectiveness results in overall cost savings (in terms of ETC) was about 160%, 61%, and 62%, compared to the basic $\overline{X}$, basic EWMA, and basic $\overline{X}$&EWMA schemes, respectively, in this study.

6. Conclusions

The reduction of GHGs emissions is considered as a major issue within the global community. Amongst all the GHGs, CO_2 is considered as the most significant contributor to the changes in global climatic conditions. Hence, researchers and professionals have intensely focused on finding suitable methods for monitoring and controlling CO_2 emissions. The industrial sector is one of the fastest-growing sources of GHGs, due to the excessive consumption of energy required to cope with the growing production of energy exhaustive products. The continuous monitoring of CO_2 emissions from different industrial facilities can be an important step in reducing carbon emissions and encouraging them to use cleaner energy. This article presents an optimal economic-statistical design of the combined $\overline{X}$&EWMA scheme for efficient monitoring of the carbon emissions from industrial facilities. The design of the proposed SPM scheme is based on emissions data collected from different industrial facilities. However, the data can also be collected from only one location, if the focus is to monitor and control a single facility. The effectiveness of the proposed optimal SPM scheme was compared with that of other monitoring schemes, namely the basic $\overline{X}$, basic EWMA, and basic $\overline{X}$&EWMA schemes. The comparison study showed that the proposed optimal $\overline{X}$&EWMA scheme reduced the expected total cost incurred owing to carbon emissions and operation of the SPM scheme by about 40%, 79%, and 29%, compared with the basic $\overline{X}$, basic EWMA, and basic $\overline{X}$&EWMA schemes, respectively. Finally, the design and application of the proposed SPM scheme are illustrated based on real data carbon emissions collected from different industrial facilities. The same SPM scheme can also be used for monitoring the emissions from other facilities in other sectors, such as transportation, building and construction, and agriculture.

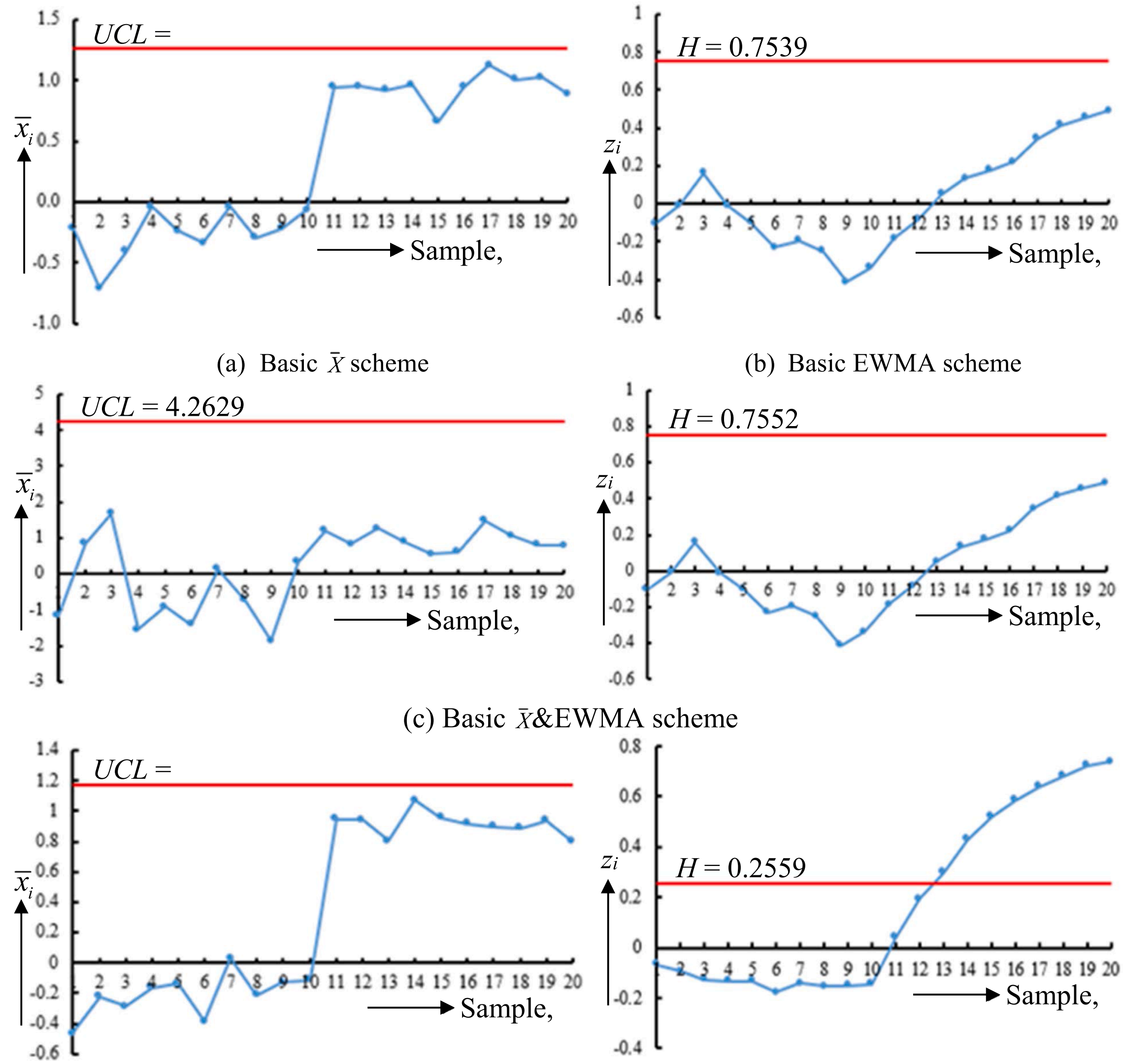
In this study, the random shift in the carbon emission process is modeled by a Rayleigh distribution. In future study, the effectiveness of the proposed SPM scheme can be investigated over other distributions of the shift, such as uniform or beta distribution. Other SPM scheme such as dual-EWMA or $\overline{X}\&CUSUM$ scheme can also be designed for monitoring the emission process, and the performance of these schemes can be compared with that of the optimal $\overline{X}\&EWMA$ scheme proposed in this study.

CRediT authorship contribution statement

Mohammad Shamsuzzaman: Conceptualization, Methodology, Software, Writing – original draft, Funding acquisition. **Ahm Shamsuzzoha:** Visualization, Validation, Writing – review & editing. **Ahmed Maged:** Visualization, Writing – review & editing. **Salah Haridy:** Methodology, Software, Writing – original draft. **Hamdi Bashir:** Investigation, Validation, Writing – review & editing. **Azharul Karim:** Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence



(a) Basic $\bar{X}$ scheme (b) Basic EWMA scheme

(c) Basic $\bar{X}$&EWMA scheme

(d) Optimal $\bar{X}$&EWMA scheme

Fig. 6. Four SPM schemes in the case study.

the work reported in this paper.

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