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An Assorted Design for Joint Monitoring of Process Parameters: An Efficient Approach for Fuel Consumption

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ABSTRACT Due to high fuel consumption, we face the problem of not only the increased cost, but it also affects greenhouse gas emission. This paper presents an assorted approach for monitoring fuel consumption in trucks with the objective to minimize fuel consumption. We propose a control charting structure for joint monitoring of mean and dispersion parameters based on the well-known max approach. The proposed joint assorted chart is evaluated through various performance measures such as average run length, extra quadratic loss, performance comparison index, and relative average run length. The comparison of the proposed chart is carried out with existing control charts, including a combination of $\bar{X}$ and S, the maximum exponentially weighted moving average (Max-EWMA), combined mixed exponentially weighted moving average-cumulative sum (CMEC), maximum double exponentially weighted average (MDEWMA), and combined mixed double EWMA-CUSUM (CMDEC) charts. The implementation of the proposed chart is presented using real data regarding the monitoring of fuel consumption in trucks. The outcomes revealed that the joint assorted chart is very efficient to detect different kinds of shifts in process behaviors and has superior performance than its competitor charts.

INDEX TERMS Control charts, CUSUM, EWMA, greenhouse gas, logistics, run length.

NOMENCLATURE

Abbreviation/ Symbol	Description
ARL	Average run length
EQL	Extra quadratic loss
PCI	Performance comparison index
CUSUM	Cumulative sum
EWMA	Exponentially weighted moving average
RARL	Relative average run length
Max-EWMA	Maximum exponentially weighted moving average
Max-CUSUM	Maximum cumulative sum
CMEC	Combined mixed exponentially weighted moving average-cumulative sum
MDEWMA	Maximum double exponentially weighted moving average
CMDEC	Combined mixed double EWMA-CUSUM
CC	Combined cumulative sum
SPC	Statistical process control
SS-DEWMA	Sum of squares double exponentially weighted moving average
K_{ME}	Design parameter for Max EWMA chart
K_2	Control limit coefficient of MDEWMA chart
K	Control limit coefficient of CUSUM chart
UCL	Upper control limit
IC	In-control
OOC	Out-of-control
RL	Run length
GHG	Greenhouse gas
EU	European Union
F	Final statistic of proposed study

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k, λ	Sensitivity parameters of proposed chart
a	Shift in mean in proposed design structure
b	Shift in dispersion in proposed design structure
μ_0	IC mean
μ_1	OOC mean
σ_0	IC standard deviation
n	Sample size
h	Decision interval
c_s	Charting constant for Shewhart in proposed study
h_c	Charting constant for CUSUM in proposed study
L_e	Charting constant for EWMA in proposed study
LT_1	Proposed statistic used to detect large shift in mean
LT_2^+	Proposed statistic used to detect positive medium shift in mean
LT_2^-	Proposed statistic used to detect negative medium shift in mean
k_{MC}	Reference value of Max- CUSUM chart
K_{SD}	Control limit coefficient of SS-DEWMA chart
K_i	Control limit coefficient of CMEC chart
LT_3	Proposed statistic used to detect small shift in mean
DT_1	Proposed statistic used to detect large shift in dispersion
DT_2^+	Proposed statistic used to detect positive medium shift in dispersion
DT_2^-	Proposed statistic used to detect negative medium shift in dispersion
DT_3	Proposed statistics used to detect small shift in dispersion
$JA_{k,\lambda}$	Joint assorted chart
(k, λ)	Sensitivity parameters

I. INTRODUCTION

One third of the total operating cost in logistics is mostly used as fuel and maintenance expense. Due to economic issues, the price of gasoline has increased, in general, in oil-dependent countries. Nowadays, many companies are facing tough financial challenges. The monitoring and control of fuel usage is an essential part of logistic operations management requiring an intensive, systematic and comprehensive approach.

In the developing countries, a substantial proportion of logistic companies do not have advanced systems that can offer them the potential for fuel saving through monitoring and management of the fuel usage of their fleets. Currently, in most of the companies, average fuel consumption is calculated in a very simple way (i.e. fuel purchased divided by total distance travelled). Many transport operators do not have systems that treat fuel as money. The basic problem with monitoring of fuel consumption of vehicles is the very rapid changes, as the fuel consumption varies minute by minute or mile by mile. There is no direct linear relation between fuel consumption and distance because it depends on several factors such as speed, load, acceleration, terrain, vehicle condition and several other drivers' related factors.

The Statistical Process Control (SPC) is a methodology used for monitoring and controlling the quality of a process through different analysis tools. Control charts are one of the prime tools in SPC that are used for controlling the unnatural variations in a process. These unnatural variations (known as shifts) in the process parameter(s) can be categorized as small, moderate and large. Generally, the Shewhart control chart efficiently detects large shifts, whereas to detect small and moderate shifts, CUSUM and EWMA are better options. A commonly used approach is to monitor each parameter separately, such as dispersion and location parameters. But in real life, we come across some situations, where joint monitoring of mean and variance parameters of a process is required.

In literature, many studies have proposed charts for the joint monitoring of location and scale parameters, for instance, see. Domangue and Patch [1], Gan [2], Albin *et al.* [3]. Max-EWMA chart for joint monitoring of process location and scale was proposed by Xie [4], while a joint EWMA chart for monitoring location and scale was proposed by Gan [5]. Reynolds Jr and Stoumbos [6] proposed three joint charts. Max-EWMA chart proposed Chen *et al.* [7] compared its *ARL* performance with a combination chart ($\bar{X}$ and S). A Max-CUSUM chart was proposed by Thaga [8] for joint monitoring, whereas Costa and Rahim [9] proposed a chart for joint monitoring of mean and dispersion parameters based on EWMA. Furthermore, Costa and Rahim [10] enhanced the proposal of Chen *et al.* [11]. Moreover, Khoo *et al.* [12] and Teh *et al.* [13] proposed Max-DEWMA and SS-DEWMA charts for joint monitoring. Recently, three charts namely CMEC, CDMEC and CC, were proposed by Zaman *et al.* [14] for the simultaneous monitoring of location and scale parameters.

The afore-mentioned approaches were designed to detect only the specific amounts of shifts (small, medium and large). Some advancement on the topic may also be seen in [15]–[24] and the references therein.

This study proposes a generalized chart based on the max approach to detect small, moderate and large amounts of shifts in the process mean and variation simultaneously. The proposal combines all the three basic structures (Shewhart, EWMA, CUSUM) both for mean and variance and targets all types of shifts in process parameter. The proposal is named as joint assorted chart for simultaneous monitoring of location and dispersion parameters.

The organization of this study outlined as follows: existing control charts for joint monitoring are discussed in Section II; performance measures are described in Section III; the design of the joint assorted chart is provided in Section IV; the performance evaluation of the joint assorted chart is demonstrated in Section V; comparative analysis of the proposed chart and existing charts is portrayed in Section VI; an application of the proposed chart is shown in Section VII; and concluding remarks are discussed in Section VIII.

II. EXISTING CONTROL CHARTS FOR JOINT MONITORING

The design structures of some existing studies for the joint monitoring (location and scale) parameters are discussed here.

A. MAX-EWMA CONTROL CHART

Max-EWMA chart was proposed by Chen *et al.* [11] for the detection of positive and negative shifts in location and/or scale parameters. The design structure of Max-EWMA control charts is given below:

$$Y_i = (1-\lambda)\,Y_{i-1} + \lambda U_i, \tag{1}$$

$$Z_i = (1-\lambda)\,Z_{i-1} + \lambda V_i,$$
$$0 < \lambda \le 1, \quad i = 1, 2, \ldots\ldots\ldots \tag{2}$$

where $Y_0 = 0, Z_0 = 0,$

$$U_i = \frac{(\bar{X}_i - \mu)}{\sigma\big/\sqrt{n_i}}, \tag{3}$$

and

$$V_i = \Phi^{-1}\left\{H\frac{(n_i-1)S_i^2}{\sigma^2}; n_i - 1\right\},$$
$$M_i = max\left\{|Y_i|, |Z_i|\right\}. \tag{4}$$

Because M_i is non-negative. Therefore, the upper control limit (UCL) is given as

$$UCL = E(M_i) + K_{ME}\sqrt{V(M_i)}$$

where K_{ME}, $E(M_i)$ and $V(M_i)$ are design parameter, the mean and the variance of M_i respectively, when the process is in-control.

B. MAX-CUSUM CHART

Thaga [8] proposed Max-CUSUM chart for simultaneous monitoring of process parameters (location and scale) by using a single monitoring statistic. The design structure of Max-CUSUM chart with respect to equations (3) and (4) are given as follows:

$$\left.\begin{aligned} \boldsymbol{C_i^+} &= \mathbf{max}\left[\mathbf{0}, \boldsymbol{U_i} - \boldsymbol{k_{MC}} + \boldsymbol{C_{i-1}^+}\right] \\ \boldsymbol{C_i^-} &= \mathbf{max}\left[\mathbf{0}, -\boldsymbol{k_{MC}} - \boldsymbol{U_i} + \boldsymbol{C_{i-1}^-}\right] \end{aligned}\right\}$$

and

$$\left.\begin{aligned} \boldsymbol{S_i^+} &= \mathbf{max}\left[\mathbf{0}, \boldsymbol{V_i} - \boldsymbol{k_{MC}} + \boldsymbol{S_{i-1}^+}\right] \\ \boldsymbol{S_i^-} &= \mathbf{max}\left[\mathbf{0}, -\boldsymbol{k_{MC}} + \boldsymbol{S_{i-1}^-}\right] \end{aligned}\right\}$$

where C_0 and S_0 are the staring points while k_{MC} is the reference value of Max-CUSUM chart. If either C_i^+ or C_i^- is greater than the decision interval (h), the process is deemed out-of-control due to changes in the process mean. Similarly, a process is declared out-of-control for the changes in process standard deviation if either S_i^+ or S_i^- is larger than the decision interval. As, U_i and V_i are standardized normally distributed, a new statistic that can simultaneously monitor process parameters (location and scale) is given as

$$M_i = max\left\{C_i^+, C_i^-, S_i^+, S_i^-\right\}$$

Since, $M_i's$ are non-negative, hence they are compared only with UCL (i.e. h), and any M_i falling outside UCL signals out-of-control.

C. MDEWMA CHART

Khoo *et al.* [12] proposed a single Max-DEWMA chart. An extended version of Max-EWMA chart was proposed by Chen *et al.* [11]. The design structure of MDEWMA chart is given below:

$$W_i = \lambda Y_i + (1-\lambda)W_{i-1}, \tag{5}$$

$$Q_i = \lambda Z_i + (1-\lambda)Q_{i-1} \tag{6}$$

where $i = 1, 2, \ldots..$, $W_0 = Q_0 = 0$, Y_i and Z_i are given in equations (1) and (2). The final statistic of MDEWMA is given as

$$L_i = max\left\{|W_i|, |Q_i|\right\}$$

There is only UCL because L_i have non-negative values, which is described below:

$$UCL = E(L_i) + K_2\sqrt{V(L_i)}$$

where $E(L_i)$ and $V(L_i)$ are the mean and variance of L_i for the in-control process respectively while K_2 is the control limit coefficient. If there is a variation in the process mean and/or scale parameter, the statistic L_i will be large and will jump out of UCL if the process goes in an out-of-control state.

D. SS-DEWMA CHART

SS-DEWMA control chart was proposed by Teh *et al.* [13], they also reviewed a single sum of square EWMA (SS-EWMA) control chart proposed by Xie [4]. The two SS-DEWMA statistics are given below:

$$P_i = \lambda Y_i + (1-\lambda)P_{i-1}, \tag{7}$$

$$Q_i = \lambda Z_i + (1-\lambda)Q_{i-1}, \tag{8}$$

where Y_i and Z_i are as given in equations (1) and (2). The starting values of P_i and Q_i are both zero, i.e. $P_0 = Q_0 = 0$.

The final statistic of SS-DEWMA is obtained by two statistics mentioned in the above equations (7) and (8):

$$L_i = P_i^2 + Q_i^2, \tag{9}$$

The UCL of this statistic is described as

$$UCL = E(L_i) + K_{SD}\sqrt{V(L_i)}$$

where $E(L_i)$ and $V(L_i)$ are the mean and the variance of L_i respectively while K_{SD} is a control limit coefficient, when the process is in-control. If the mean and/or variance go out-of-control, then L_i will fall outside the UCL.

E. THE CMEC, CMDEC AND CC CONTROL CHART

Zaman *et al.* [14] proposed three different approaches to monitor location and scale parameters. Here we outline the plotting statistics and control limits of these approaches.

The EWMA structures for location and dispersion are given in equations (1) and (2), respectively. The classical CUSUM statistics for location and dispersion are, respectively, given as:

$$\left.\begin{aligned} L_i^+ &= \max\left[0, (U_i-\mu) - K + L_{i-1}^+\right] \\ L_i^- &= \min\left[0, (U_i-\mu) + K + L_{i-1}^-\right] \end{aligned}\right\}, \qquad (10)$$

$$\left.\begin{aligned} D_i^+ &= \max\left[0, (V_i-\mu) - K + D_{i-1}^+\right] \\ D_i^- &= \min\left[0, (V_i-\mu) + K + D_{i-1}^-\right] \end{aligned}\right\}, \qquad (11)$$

where K is the optimal parameter for detecting shifts. The output values of equations (3) and (4) are considered as an input value of CUSUM structure in equations (10) and (11). The plotting statistics of CMEC control chart are defined as:

$$\left.\begin{aligned} CMECL_i^+ &= \max\left[0, (Y_i-\mu) - K_i + CMECL_{i-1}^+\right] \\ CMECL_i^- &= \min\left[0, (Y_i-\mu) + K_i + CMECL_{i-1}^+\right] \end{aligned}\right\}, \qquad (12)$$

$$\left.\begin{aligned} CMECV_i^+ &= \max\left[0, (Z_i-\mu) - K_i + CMECV_{i-1}^+\right] \\ CMECV_i^- &= \min\left[0, (Z_i-\mu) + K_i + CMECV_{i-1}^+\right] \end{aligned}\right\}, \qquad (13)$$

where $K_i = k_{cmec} * \sqrt{Var(Y_i)}$ and k_{cmec} represents a constant coefficient. These statistics are plotted against $(\pm H_i)$. The process is deemed out-of-control if:

$$CMECL_i^+ \text{ or } CMECV_i^+ > (H_i), \text{ or}$$
$$CMECL_i^- \text{ or } CMECV_i^- < (-H_i).$$

Zaman *et al.* [14] also discussed the one-sided proposed structure of these statistics which are defined as

$$\left.\begin{aligned} CMECL_i^+ &= \max[0, (Y_i-\mu) - K_i + CMECL_{i-1}^+] \\ CMECL_i^- &= \max[0, -(Y_i-\mu) - K_i + CMECL_{i-1}^-] \end{aligned}\right\}, \qquad (14)$$

$$\left.\begin{aligned} CMECV_i^+ &= \max[0, (Z_i-\mu) - K_i + CMECV_{i-1}^+] \\ CMECV_i^- &= \min[0, -(Z_i-\mu) - K_i + CMECV_{i-1}^-] \end{aligned}\right\}, \qquad (15)$$

For these modified statistics only H_i is used as the control limit. Any of these statistics exceeding the limit indicate out-of-control scenario.

F. CONTROL CHARTING STRUCTURE OF CMDEC

The control charting structure of CMDEC is the modification of Chen *et al.* [11] and Khoo *et al.* [12]. For the CMDEC control chart structure, the statistics defined in equations (5) and (6) are considered as input statistics in the CUSUM chart. The following statistics of CMDEC are used for mean and variance monitoring, respectively.

$$\left.\begin{aligned} CMDECL_i^+ &= \max[0, (W_i-\mu) - K_{1i} + CMDECL_{i-1}^+] \\ CMDECL_i^- &= \min[0, (W_i-\mu) + K_{1i} + CMDECL_{i-1}^-] \end{aligned}\right\}, \qquad (16)$$

$$\left.\begin{aligned} CMDECV_i^+ &= \max\left[0, (Q_i-\mu) - K_{1i} + CMDECV_{i-1}^+\right] \\ CMDECV_i^- &= \min\left[0, (Q_i-\mu) + K_{1i} + CMDECV_{i-1}^-\right] \end{aligned}\right\}, \qquad (17)$$

where $K_{1i} = k_1\sigma_{w_i}^2$, k_1 is the coefficient like k_{cmec} and $\pm H_{D_i}$ are the control limits for CMDEC control chart. The decision procedure remains the same as that of the CMEC control chart.

G. CONTROL CHARTING STRUCTURE OF CC

The CC is a special case of CMEC and CMDEC control charts, CMEC and CMDEC charts become classical CUSUM chart for smoothing constant $(\lambda = 1)$. The control charting structure of CC is defined as:

$$\left.\begin{aligned} CCL_i^+ &= \max[0, (U_i-\mu) - K_{2i} + CCL_{i-1}^+] \\ CCL_i^- &= \min[0, (U_i-\mu) + K_{2i} + CCL_{i-1}^-] \end{aligned}\right\}, \qquad (18)$$

$$\left.\begin{aligned} \boldsymbol{CCV_i^+} &= \mathbf{max}[0, (\boldsymbol{V_i}-\boldsymbol{\mu}) - \boldsymbol{K_{2i}} + \boldsymbol{CCV_{i-1}^+}] \\ \boldsymbol{CCV_i^-} &= \mathbf{min}[0, (\boldsymbol{V_i}-\boldsymbol{\mu}) + \boldsymbol{K_{2i}} + \boldsymbol{CCV_{i-1}^-}] \end{aligned}\right\}, \qquad (19)$$

where K_{2i} is the same as K_i and K_{1i}. The control limits of CC chart are $\pm H_2$.

III. PERFORMANCE MEASURES

The performance of control charts is evaluated using some useful performance measures. In this section, a brief outline is given about these measures.

Assume X is a normally distributed random variable, $X_{ij} \sim N\left(\mu_0 + a\sigma_0, b^2\sigma_0^2\right)$, $i = 1, 2, \ldots\ldots..$ and $j = 1, 2, \ldots., n$. It is to be mentioned here that: $a = 0$ and $b = 1$ refers to an in-control (IC) model; $a \neq 0$ and/or $b \neq 1$ refers to an out-of-control (OOC) model.

The shift in mean can be defined as $a = (\mu_1 - \mu_0)/\left(\sigma_0/\sqrt{n}\right)$, where μ_0 is IC mean, μ_1 (shifted mean) is OOC mean defined as $\mu_1 = \mu_0 + a\left(\sigma_0/\sqrt{n}\right)$, where σ_0 and n represent IC standard deviation and sample size, respectively. Similarly, a shift in the dispersion can be defined as: $b = \sigma_1/\sigma_0$. Where σ_0 is IC standard deviation, σ_1 is OOC standard deviation, defined as: $\sigma_1 = b\sigma_0$. Using the aforementioned terminologies, we discuss here some performance measures.

A. RUN LENGTH (RL)

A series of points plotted on a graph until an OOC signal is indicated known as a run. The number of points in a run is called run length. Furthermore, RL has two main states, namely IC state and OOC state. A greater in-control RL indicates a lower false alarm rate, and a smaller out-of-control RL indicate better detection ability of a charting scheme.

B. AVERAGE RUN LENGTH (ARL)

The most frequent performance measure used in control charts is ARL. The average amount of sample points awaited until the first out-of-control signal happens. In addition, ARL classified into two types, ICARL(ARL_0) and OOC ARL (ARL_1).

ARL_0 needs to be maximized to delay the false alarm as far as feasible when the process is IC, while OOC ARL (ARL_1) is required to be minimized to detect the signal at the earliest for OOC process.

C. EXTRA QUADRATIC LOSS (EQL)/

The EQL is described as the weighted average ARL for the domain of shifts $(0 < a \leq a_{max}, 1 < b \leq b_{max})$ by considering the square of shift $(a^2 + b^2 - 1)$ as weight. Mathematically , EQL is described as:

$$EQL = \frac{1}{a_{max}.(b_{max} - 1)} \int_0^{a_{max}} \int_1^{b_{max}} \times (a^2 + b^2 - 1) ARL\,(a, b)\, da db,$$

D. PERFORMANCE COMPARISON INDEX (PCI)

The proportion of a chart's EQL and a chart with minimal EQL $(EQL_{benchmark})$ is known as PCI.

$$PCI = \frac{\boldsymbol{EQL}}{\boldsymbol{EQL_{benchmark}}},$$

For the benchmark chart $PCI = 1$ while for other charts, it deviates from 1. If $PCI > 1$, the competing chart is considered as inferior than the benchmark, and otherwise superior.

For more details on the above-mentioned performance index, see [25]–[27].

IV. THE DESIGN STRUCTURE OF JOINT ASSORTED CHART ($JA_{K,\lambda}$)

The design structure of the joint assorted chart to monitor location and scale parameters with the aim to detect the different amount of shifts (small, moderate and large) in a single control charting structure is given below:

A. LOCATIONS

The following statistics of location (for Shewhart, CUSUM and EWMA charts) in joint assorted chart are given as:

$$\text{Shewhart}: \bar{X}_i = \frac{\sum_{j=1}^{n} X_{ij}}{n}$$

$$\text{CUSUM}: \left.\begin{aligned} C_i^+ &= \max[0, (\bar{X}_i - \mu_0) - k\frac{\sigma_0}{\sqrt{n}} + C_{i-1}^+] \\ C_i^- &= \min[0, (\bar{X}_i - \mu_0) + k\frac{\sigma_0}{\sqrt{n}} + C_{i-1}^-] \end{aligned}\right\}$$

$$\text{EWMA}: Z_i = \lambda \bar{X}_i + (1 - \lambda) Z_{i-1}$$

Let $\boldsymbol{LT_1}$ statistic is used to detect a large amount of shift in the process location and it is defined as:

$$LT_{1\mathrm{i}} = \left|\frac{v_i}{c_s}\right|, \tag{20}$$

where c_s represents charting constant for Shewhart chart and U_i is as defined in equation (3). The following statistics are used for detecting medium shift in the process mean:

$$LT_{2\mathrm{i}}^+ = \frac{C_i^+}{h_c \frac{\sigma_0}{\sqrt{n}}}, LT_{2\mathrm{i}}^- = \frac{C_i^-}{h_c \frac{\sigma_0}{\sqrt{n}}}, \tag{21}$$

where h_c is the CUSUM charting constant. Likewise, to detect a small amount of shift in the process mean, used the following statistic:

$$\boldsymbol{LT_{3\,i}} = \left|\frac{\boldsymbol{Z_i - \mu_0}}{\boldsymbol{L}}\right|, \tag{22}$$

where $= L_e \frac{\sigma_0}{\sqrt{n}} \left[\sqrt{\frac{\lambda}{2-\lambda}\left[1 - (1 - \lambda)^{2i}\right]}\right]$, where $0 < \lambda \leq 1$ and L_e is the charting constant for EWMA chart.

B. VARIABILITY

The large shift in process variability is detected by the statistics DT_1 defined as:

$$DT_{1i} = \frac{V_i}{C_s} \tag{23}$$

where c_s is Shewhart chart control limit coefficient and V_i as defined in equation (4). Let DT_2^+ and DT_2^- are the statistics used to detect the moderate shifts in the process variability. These statistics are defined as:

$$\begin{aligned} DT_{2i}^+ &= \max\left[0, V_i - k + DT_{2i-1}^+\right]/h_c, \\ DT_{2i}^- &= \max\left[0, -V_i - k + DT_{2i-1}^-\right]/h_c, \end{aligned} \tag{24}$$

where h_c is CUSUM control limit coefficient and k is the optimal parameter for detecting medium shifts. The small amount of shift in process variance is detected by the following

$$DT_{3i} = (\lambda V_i + (1 - \lambda)\, DT_{3i-1})/L_e \sqrt{\frac{\lambda}{2-\lambda}\left[1 - (1 - \lambda)^{2i}\right]} \tag{25}$$

where L_e and λ (between 0 and 1) represent the control limit coefficient and sensitivity parameter respectively for EWMA.

Assume F_i is the ultimate plotting statistic of the proposed chart which consists of location and dispersion statistics given as:

$$F_i = \max(LT_{1i}, LT_{2i}^+, LT_{2i}^-, LT_{3i} DT_{1i}, DT_{2i}^+, DT_{2i}^-, DT_{3i}) \tag{26}$$

In equation (26), F will have the maximum positive value of the eight statistics (as mentioned above). Therefore, it has only upper control limit and its limit is defined as:

$$\boldsymbol{UCL = 1} \tag{27}$$

Any point F_i exceeding 1 shows an OOC signal in the process location and/or scale parameters.

The rationale for UCL=1: It is interesting to note the rationale for selecting 1 as UCL, and it is outlined below:

As $F_i = \max(LT_{1i}, LT_{2i}^+, LT_{2i}^-, LT_{3i} DT_{1i}, DT_{2i}^+, DT_{2i}^-, DT_{3i})$ (cf. equation (26)), so $F_i > 1$ indicates the following:

- *either* $LT_{1i} > 1$ and/or $DT_{1i} > 1$ (cf. equations (20) & (23)) ⇒ the Shewhart statistic exceed their corresponding control limit c_s for location/dispersion parameters;
- *and/or* $LT_{2i}^+ or LT_{2i}^- > 1$ and/or $DT_{2i}^+ or DT_{2i}^- > 1$ (cf. equations (21) & (24)) ⇒ the CUSUM statistic exceed their corresponding control limit h_c for location/ dispersion parameters;
- *and/or* $T_{3i} > 1$ and/or $DT_{3i} > 1$ (cf. equations (22) & (25)),⇒ the EWMA statistics go beyond its respective control limit L for location and/or scale parameters.

TABLE 1. Sensitivity parameters and category of shifts.

Sensitivity Parameter	Category of shifts		
	Small	Medium	Large
λ	0.03 to 0.2	0.21 to 0.5	0.51 to 1
k	0.1 to 0.75	0.76 to 1.5	more than 1.5

The sensitivity of the proposed chart relies on the choice of design parameters (k, λ). For that purpose, we will represent our proposed chart by $JA_{k,\lambda}$. In this study, sensitivity parameters (k, λ) are listed in 17 different cases with the objective to detect a small, moderate and large amount of shifts.

Three kinds of charting constants are used to identify large, medium, and small shifts in the process mean and/or dispersion parameters. Different types of shifts and sensitivity parameters are portrayed in Table 1.

Our next task is to work out an optimal combination to set the control limit coefficients (h_c, L_e, c_s) after choosing an apt choice of sensitivity parameters (k, λ). For this purpose, the following optimality criteria is adopted:

Objective function: $\min(EQL)$

Subject to: $ARL_0 = \tau$ such that $ARL_s = ARL_e = ARL_c$.

where ARL_s, ARL_e and ARL_c refer to the ARL values respectively for the Shewhart, EWMA and CUSUM charts.

In an IC state (i.e.$a = 0$ and $b = 1$) for a fixed ARL_0 (e.g. $ARL_0 = 185$) the control limit coefficients (h_c, L_e, c_s) need to be adjusted accordingly for $JA_{k,\lambda}$ control chart. For this purpose, 17 distinct cases of sensitivity parameters (k, λ) are used and we worked out the triplets (h_c, L_e, c_s) for $JA_{k,\lambda}$ control chart. The combinations (h_c, L_e, c_s) are selected so that the ARL_0 of six individual charts are exactly same, which discards the possibility of either of them being fully- or semi-redundant. The resulting control charting constants (h_c, L_e, c_s) are portrayed in Table 2 for 17 distinct cases (combinations) of (k, λ) for the two well-known selection of $ARL_0 = 185$ and $ARL_0 = 250$.

Special Cases:

It is interesting to note that the following charts become special cases, under the said conditions, of our proposed $JA_{k,\lambda}$ chart as listed below:

- *Shewhart's joint* $(\bar{X}, S^2)$ *chart, when* h_c and L_e approaches to ∞;
- *CUSUM joint* $\left(\bar{X}, S^2\right)$ *chart, when* c_s and L_e approaches to ∞;
- *EWMA joint* $(\bar{X}, S^2)$ *chart, when* c_s and h_c approaches to ∞.

V. PERFORMANCE EVALUATIONS

In this section, we will present the performance evaluation and comparison of the proposed chart with existing charts. The competitor charts include (Max-EWMA, Max-EWMA,

TABLE 2. Charting constant at $ARL_0 = 185$ and $ARL_0 = 250$.

Case	k	λ	$ARL_0 = 185$			ARL_0=250		
			h_c	L_e	c_s	h_c	L_e	c_s
1	0.25	0.25	9.7787	3.1932	3.2685	10.3997	3.2891	3.3571
2		0.38	9.7403	3.2306	3.2629	10.3369	3.3196	3.3483
3		0.55	9.6924	3.2457	3.2559	10.2884	3.3326	3.3414
4	0.5	0.25	5.5842	3.1634	3.2411	5.8962	3.2594	3.3296
5		0.38	5.5960	3.2114	3.2445	5.9133	3.3052	3.3344
6		0.55	5.6018	3.2357	3.2461	5.9048	3.3231	3.3320
7	0.75	0.05	3.9749	2.8705	3.2804	4.1611	2.9725	3.3587
8		0.13	3.9113	3.0695	3.2534	4.1069	3.1655	3.3361
9		0.25	3.8503	3.1483	3.2272	4.0673	3.2484	3.3195
10		0.38	3.8461	3.1914	3.2254	4.0564	3.2849	3.3149
11		0.55	3.8419	3.2127	3.2236	4.0601	3.3072	3.3164
12	1	0.05	2.9838	2.8647	3.2760	3.1466	2.9835	3.3672
13		0.13	2.9456	3.0706	3.2543	3.0948	3.1682	3.3384
14		0.25	2.9044	3.1521	3.2307	3.0554	3.2451	3.3164
15	1.25	0.05	2.3487	2.8556	3.2691	2.4721	2.9700	3.3567
16		0.13	2.3237	3.0668	3.2511	2.4444	3.1669	3.3372
17		0.25	2.2817	3.1412	3.2207	2.4136	3.2440	3.3154

TABLE 3. Average run length of the $Joint\ Assorted_{k,\lambda}$ chart $ARL_0 = 185$.

k	λ	b	a = 0	0.25	0.5	1	1.5	2	EQL
0.25	0.25	0.25	2.08	2.09	2.07	1.99	1.23	1.00	3.46
		0.5	5.62	5.61	5.43	2.57	1.36	1.01	
		1	185.02	25.86	8.81	2.69	1.50	1.10	
		1.5	5.47	5.04	4.04	2.36	1.55	1.19	
		2	2.17	2.13	2.01	1.70	1.40	1.20	
0.5	0.55	0.25	2.33	2.34	2.34	2.23	1.29	1.00	3.58
		0.5	12.35	12.12	7.49	3.02	1.41	1.01	
		1	185.78	31.09	8.89	2.96	1.55	1.11	
		1.5	5.60	5.21	4.20	2.47	1.60	1.21	
		2	2.25	2.21	2.09	1.75	1.42	1.21	
0.75	0.38	0.25	2.12	2.12	2.13	2.04	1.22	1.00	3.50
		0.5	6.90	6.95	6.10	2.65	1.37	1.00	
		1	185.79	40.24	9.08	2.73	1.50	1.10	
		1.5	5.33	4.89	3.97	2.35	1.55	1.19	
		2	2.16	2.12	2.01	1.70	1.40	1.20	
1	0.13	0.25	1.95	1.94	1.94	1.86	1.11	1.00	3.32
		0.5	4.79	4.78	4.60	2.37	1.28	1.00	
		1	184.82	28.41	7.78	2.51	1.43	1.08	
		1.5	4.94	4.56	3.71	2.21	1.49	1.17	
		2	2.06	2.03	1.92	1.63	1.36	1.18	
1.25	**0.05**	0.25	1.77	1.75	1.77	1.72	1.02	1.00	**3.11**
		0.5	4.13	4.19	3.96	2.10	1.16	1.00	
		1	184.96	21.17	6.26	2.17	1.23	1.05	
		1.5	4.48	4.13	3.36	2.03	1.40	1.13	
		2	1.92	1.88	1.79	1.53	1.30	1.14	

joint $(\bar{X}, S)$, MDEWMA, CMEC and CMDEC) charts. We used various performance measures depending on run length (as discussed in Section III) including *ARL*, *EQL* and *PCI*.

We have discussed many OOC scenarios in order to assess these measures by considering varying values of shifts a and b ranging between 0 to 2 for three types of shifts (small, moderate and large).

For these measures, the computational algorithm is provided as:

(i) Generate random samples from a parent distribution (e.g. normal);
(ii) Calculate the sample statistics (which are the plotting statistics);
(iii) Set the control limits of the control chart;
(iv) Repeat steps (i)–(iii), implement the procedural steps of RL based on λ and k options (cf. Table 2);
(v) Based on step (iv) RLs, use the definitions provided in section III to calculate the measures at specific shifts, i.e. *ARL*.
(vi) Based on the outcomes of step (v) for *ARL*, evaluate the overall measures (such as EQL as described in Section III) using a suitable numerical integration method (such as Simpson or Trapezoidal).

A. PERFORMANCE ANALYSIS OF $JA_{k,\lambda}$ CHART

The efficiency of the joint assorted ($JA_{k,\lambda}$) chart is assessed using various measures such as *ARL* and *EQL* for different combinations of k, λ and at varying values of a & b. The outcomes are provided in Tables 3 and 4 at $ARL_0 = 185$ and $ARL_0 = 250$ respectively. The results reveal the following:

- The $JA_{k,\lambda}$ chart is sensitive to small, medium and large shifts (cf. Tables 3 and 4).
- The sensitivity analysis advocates that case 15 is an appropriate choice among the distinct combination of (k, λ) because it has smaller EQLs at $ARL_0 = 185$ and $ARL_0 = 250$ ((3.11 and 3.22 respectively) (cf. Tables 3- 4).
- It is to be mentioned that in comparative analysis, case 15 will be considered for comparisons with the competing charts at $ARL_0p = 250$. The charting constants of this optimal choice are ($h_c = 2.3487, L_e = 2.8556, c_s = 3.2691$) and ($h_c = 2.4721,$

TABLE 4. Average run length of the $Joint\ Assorted_{k,\lambda}$ chart $ARL_0 = 250$.

k	λ	b	a = 0	0.25	0.5	1	1.5	2	EQL
		0.25	2.18	2.18	2.18	2.10	1.36	1.00	
		0.5	6.01	6.00	5.79	2.71	1.45	1.01	
0.25	0.25	1	250.10	28.20	9.44	2.83	1.55	1.12	3.58
		1.5	5.88	5.43	4.31	2.46	1.60	1.22	
		2	2.26	2.21	2.10	1.76	1.44	1.22	
		0.25	2.48	2.48	2.48	2.35	1.41	1.00	
		0.5	14.92	14.37	8.04	3.26	1.48	1.01	
0.5	0.55	1	250.88	34.38	9.44	3.10	1.60	1.13	3.71
		1.5	5.98	5.55	4.49	2.59	1.64	1.23	
		2	2.35	2.30	2.18	1.81	1.46	1.23	
		0.25	2.23	2.22	2.24	2.15	1.36	1.00	
		0.5	7.75	7.65	6.63	2.81	1.44	1.01	
0.75	0.38	1	250.01	46.80	9.70	2.86	1.55	1.12	3.63
		1.5	5.72	5.28	4.22	2.45	1.60	1.22	
		2	2.25	2.21	2.09	1.76	1.44	1.22	
		0.25	2.04	2.04	2.04	1.95	1.20	1.00	
		0.5	5.06	5.09	4.87	2.51	1.34	1.00	
1	0.13	1	250.32	32.33	8.33	2.63	1.48	1.10	3.44
		1.5	5.30	4.91	3.97	2.32	1.53	1.19	
		2	2.15	2.11	2.00	1.69	1.39	1.19	
		0.25	1.85	1.86	1.85	1.79	1.04	1.00	
		0.5	4.43	4.45	4.30	2.24	1.21	1.00	
1.25	**0.05**	1	250.95	23.97	7.31	2.39	1.39	1.07	**3.22**
		1.5	4.85	4.46	3.59	2.14	1.45	1.15	
		2	2.00	1.97	1.87	1.59	1.33	1.16	

$L_e = 2.9700, c_s = 3.3567$) with sensitivity parameter $k = 1.25$ and $\lambda = 0.05$. (cf. Table 2).

VI. COMPARATIVE ANALYSIS

We provide comparative analysis of $JA_{k,\lambda}$ chart with Max-EWMA, Max-CUSUM, Combination of $(\bar{X}, S)$, MDEWMA, CMEC and CMDEC charts. The comparative assessment is based on two techniques: firstly, based on individual measures; secondly, based on overall measures. The performance indices in the form of ARL, EQL and PCI of the $JA_{k,\lambda}$ chart and competing charts are provided in Table 5. The findings support the following:

- Among all the competing charts, the joint assorted chart ($JA_{k,\lambda}$) has the lowest ARL_1 values for monitoring joint shifts in process location and/or scale parameters. For example, the ARL_1 values of $JA_{k,\lambda}$ chart are 1.85, 1.86, 1.85, 1.79 and 1 at $b = 0.25$ and varying choices of $a = 0, 0.25, 0.5, 1, 2$ respectively (cf. Table 5).
- The MDEWMA chart is the second-best chart in terms of detection ability. For instance, the ARL_1 values of MDEWMA chart are 1.90, 1.90, 1.90, 1.80 and 1.00 at $b = 1.5$ and different range of $a = 0, 0.od25, 0.5, 1, 2$ respectively.
- Similarly, the ARL_1 values of the $JA_{k,\lambda}$ chart at $b = 1.5$ and varying choices of $a = 0, 0.25, 0.5, 1, 2$ are 4.85, 4.46, 3.59, 2.14 and 1.15 respectively, while the corresponding ARL_1 values of MDEWMA chart are 5.50, 5.00, 3.90, 2.20 and 1.20.
- The $JA_{k,\lambda}$ chart with $k = 1.25$ and $\lambda = 0.05$ is regarded as the benchmark chart because it has minimum EQL value (i.e. 3.22) as compared to the other competing charts.
- The $JA_{1.25,0.05}$ chart has PCI equal to 1, while the PCI values of existing counterpart charts such as Max-EWMA, Max-CUSUM, Combination of $(\bar{X}, S)$, MDEWMA, CMEC and CMDEC charts are 2.16, 1.86, 2.23, 1.07, 3.35 and 1.37, respectively (cf. Table 5). It shows that the proposed chart is superior to the other competing charts for the joint monitoring of location and scale parameters.

VII. APPLICATION: MONITORING THE FUEL EFFICIENCY OF TRUCKS

An implementation of the proposed chart is presented for monitoring fuel efficiency of trucks. Nowadays, global warming is one of the biggest challenges for us. To overcome this

TABLE 5. ***ARL's*, *EQL's* and *PCI's* comparison of proposed and competing charts at $ARL_0 = 250$.**

Charts	b	a = 0	0.25	0.5	1	2	EQL	PCI
	0.25	1.85	1.86	1.85	1.79	1.00		
	0.5	4.43	4.45	4.30	2.24	1.00		
Joint Assorted	1	250.95	23.97	7.31	2.39	1.07	**3.22**	**1**
	1.5	4.85	4.46	3.59	2.14	1.15		
	2	2.00	1.97	1.87	1.59	1.16		
	0.25	4.00	3.90	4.00	3.0	2.10		
	0.5	6.90	6.90	6.80	4.50	2.30		
Max-EWMA	1	251.60	24.10	9.90	4.60	2.40	6.94	2.16
	1.5	8.60	8.20	7.10	4.60	2.50		
	2	4.40	4.40	4.20	3.70	2.50		
	1	250.02	18.52	7.66	3.19	1.59		
Max-CUSUM	1.5	9.61	11.66	5.28	2.41	1.35	6.00	1.86
	2	6.64	8.46	4.12	2.04	1.24		
	0.25	3.00	3.00	3.10	3.10	2.10		
	0.5	6.10	6.10	6.00	4.40	2.30		
Combination $(\bar{X}, S)$	1	249.60	24.20	9.90	4.70	2.40	7.17	2.23
	1.5	10.70	10.10	8.00	4.70	2.50		
	2	5.90	5.80	5.50	4.30	2.50		
	0.25	1.90	1.90	1.90	1.80	1.00		
	0.5	5.00	5.00	4.70	2.30	1.00		
MDEWMA	1	250.00	42.90	8.90	2.50	1.10	3.45	1.07
	1.5	5.50	5.00	3.90	2.20	1.20		
	2	2.10	2.10	2.00	1.60	1.20		
	0.25	6.34	6.33	6.33	6.33	4.00		
	0.5	10.25	10.27	10.2	7.14	3.95		
CMEC	1	251.88	26.85	13.5	7.2	3.86	10.80	3.35
	1.5	11.9	11.56	10.43	7.15	3.88		
	2	6.57	6.64	6.5	5.88	3.88		
	0.25	2.83	2.82	2.82	2.78	1.16		
	0.5	5.5	5.51	5.41	3.24	1.31		
CMDEC	1	249.49	24.45	8.33	3.35	1.41	4.42	1.37
	1.5	6.66	6.3	5.31	3.25	1.45		
	2	2.94	2.91	2.79	2.38	1.45		

issue many strategies, workshops, training and researches are going on. The CO_2 emission is one of the key elements in global warming. The need of the hour is to reduce greenhouse gas (GHG) emission in logistic industry.

Most of the transporters are monitoring their fuel consumption manually; only one out of ten are using advanced technology monitoring system [28]. Cost also plays a significant role in an organization and through the efficient monitoring of fuel consumption, an organization can save money, labor work and time. The objective of the European Union's (EU's) is to reduce GHG logistics by 60% in 30 years. According to a report [29], heavy-duty trucks discharge 5% of the EU total GHG emission. The freight industry has very few energy efficiency methods $ARL_0 = 250ab(\bar{X}S)$ (cf. Liimatainen [30]). Fig. 1 presents a pictorial display of fuel trucks in action, their monitoring system, and some related environmental issues along with some useful statistics of contributions of various components.

We have used a real data set related to a supply chain service provider company, with the aim to monitor the fuel consumption of its fleet. For the said purpose, we got fuel consumption information on 135 trucks. 100 of these trucks were weighing 11 tons, whereas 35 were weighing 30 tons. Using these 135 observations, 35 subgroups each of size 5 are created. For the purpose of illustration, we constructed the joint assorted, the Max-CUSUM and the CC charts respectively, for this real dataset. The control chart factors and limits of these charts are computed considering information

FIGURE 1. **Fuel trucks, their monitoring system, and environmental issues with some useful statistics of contributions of various components: (a) ICGET 2018: [31]; (b) https://inhabitat.com/japan-tests-driverless-trucks-report-shows-15-less-fuel-consumption;(c). https://www.picswe.com/pics/fuel-monitoring-system-8d.html.**

on 11 ton trucks as the in-control data. Specifically, we have considered the following:

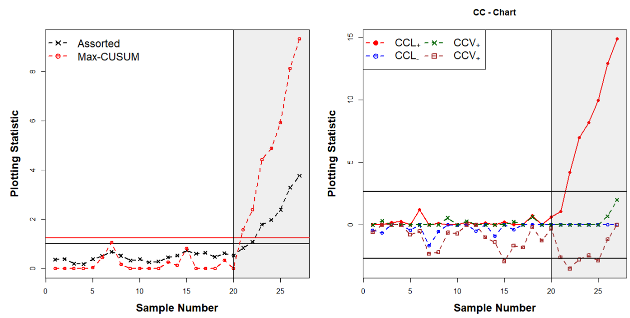
- For the proposed Assorted $A_{1.25,0.05}$ chart, we used $k = 1.25$, $\lambda = 0.05$, $h_c = 2.4721$, $L_e = 2.9700$ and $c_s = 3.3567$ and $UCL = 1$;
- For the Max-CUSUM chart, we used $k = 1.25$, and $UCL = 1.245$.
- For the CC chart, we used $k = 0.5$, and the lower and upper control limits are set as -2.685 and 2.685, respectively.

These control chart factors and limits are selected to get the $ARL_0 = 370$ for all the charts, after standardization. From the control chart displays in Fig. 2 (a), we can observe that there is a big shift in the last 7 samples and all three charts are equally efficient for the detection of such shift level.

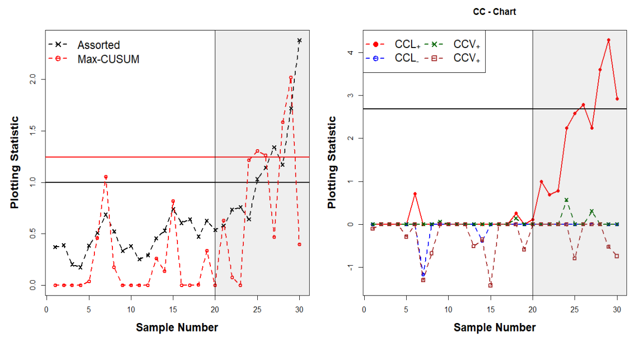
Further, to investigate these charts for the detection of other shift levels, the control limits were computed using the first 20 samples, and 10 new samples were simulated with different shift levels (small to moderate). Specifically, we considered three cases.

- A shift with magnitude $a = 0.5$ in the process location parameter (Fig. 2(b)).

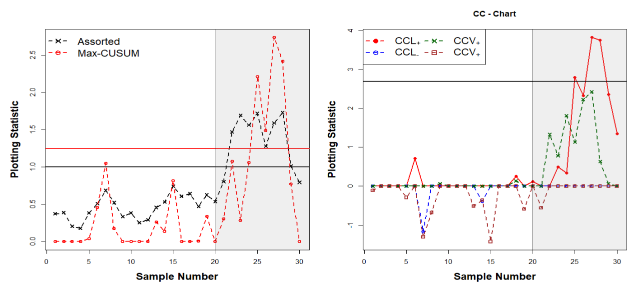
(a). Charts referring to 20 in-control subgroups and 7 out of control subgroups (with the larger shift - almost 3 sigma)



(b). Charts referring to 20 in-control subgroups and 7 out of control subgroups (with 0.5 sigma shift in location)



(c). Charts referring to 20 in-control subgroups and 7 out of control subgroups (with 1.8 sigma shift in dispersion)



(d). Charts referring to 20 in-control and 7 out of control subgroups (with 0.3 sigma shift in location and 1.3 sigma shift in dispersion)

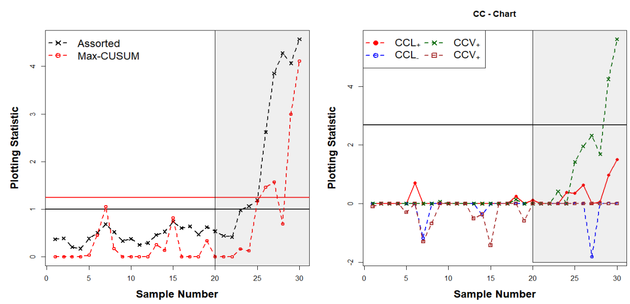


FIGURE 2. **Control charts to monitor the fuel consumption of trucks for various amounts of shifts in location and dispersion.**

- A shift with magnitude $b = 1.8$ in the process dispersion parameter (Fig. 2(c)).
- The joint shift of magnitudes $a = 0.3$ and $b = 1.3$ in the process location and dispersion, respectively (Fig. 2(d)).

Fig. 2(b) indicates that to detect 0.5 sigma shifts in the process location, the joint assorted chart, the Max-CUSUM chart and the CC chart respectively detect 6, 4 and 3 out-of-control points. CUSUM and the CC charts respectively detect 7, 5 and 2 out-of-control points.

Fig. 2(d) indicates that to detect joint shift, 0.3 sigma in mean and 1.8 sigma shift in the process dispersion parameter, the joint assorted, the Max-CUSUM and the CC charts respectively detect 7, 5 and 3 out-of-control points.

This superiority of the joint assorted chart is indicative of the fact that our newly proposed $JA_{k,\lambda}$ chart is efficient to detect different amounts of shifts (small to large) in the process mean and/or variance parameters. This finding is consistent with the results in Section VI.

VIII. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

The study presents a joint assorted control chart for joint monitoring of mean and/or variance parameters. By using various performance measures such as *ARL*, *EQL*, *RARAL* and *PCI*, the joint assorted control chart is compared with the existing charts (Max-EWMA, MDEWMA, a combination of $\bar{X}$ and S, CMEC, CMDEC charts). The comparative assessment showed that the $JA_{k,\lambda}$ chart efficiently detects different amounts of shifts in process location and/or scale, and it outperforms all the competitor charts. An application of the proposed chart related to the fuel consumption of trucks (environmental/financial impacts and optimum fuel consumption) highlights the significance of our proposal for the monitoring of real processes.

The scope of the present research may be extended to multivariate monitoring of multiple quality characteristics of interest. Moreover, nonparametric charts under assorted setup is another interesting direction to be explored.

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