



**ARTICLE**

## Control Charts for the Shape Parameter of Power Function Distribution under Different Classical Estimators

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### ABSTRACT

In practice, the control charts for monitoring of process mean are based on the normality assumption. But the performance of the control charts is seriously affected if the process of quality characteristics departs from normality. For such situations, we have modified the already existing control charts such as Shewhart control chart, exponentially weighted moving average (EWMA) control chart and hybrid exponentially weighted moving average (HEWMA) control chart by assuming that the distribution of underlying process follows Power function distribution (PFD). By considering the situation that the parameters of PFD are unknown, we estimate them by using three classical estimation methods, i.e., percentile estimator (P.E), maximum likelihood estimator (MLE) and modified maximum likelihood estimator (MMLE). We construct Shewhart, EWMA and HEWMA control charts based on P.E, MLE and MMLE. We have compared all these control charts using Monte Carlo simulation studies and concluded that HEWMA control chart under MLE is more sensitive to detect an early shift in the shape parameter when the distribution of the underlying process follows power function distribution.

### KEYWORDS

Average run length; control chart; percentile estimator; power function distribution

## 1 Introduction

The reliability engineer is very keen on the quality of manufactured products. There is always some variation observed in the output of the process. This variation may be classified as the natural and unnatural cause. Statistical process control (SPC) is helpful in reducing the unnatural causes of the failures of products. In statistical process control, two types of control charts are mainly used to reduce such unnatural causes. One type of control charts is called a memory type control chart, and the second one is memory less control chart. Memory type control charts are exponentially weighted moving averages control chart, and hybrid exponentially weighted moving average control chart. Memory less control chart that is mainly used is the Shewhart control chart. Both types of control charts assume that the distribution of the quality characteristic during the process is normal. A lot of work has done in this regard, such as the EWMA control charts, firstly by Roberts [1] and recently by Li et al. [2] and Nguyen et al. [3]. The cumulative-sum



(CUSUM) control chart firstly by Page [4], and recently by [5–7]. The mixed EWMA-CUSUM control charts by [8,9]; and the hybrid exponential weighted moving average (HEWMA) control charts due to Shamma et al. [10], and Haq [11]. All of these are based on the assumption of normality of the process.

In a real life scenario, this is not always possible to fulfil the normality assumption for the distributions of error during the process. A very few work in literature is about this situation including [12–18].

Power function distribution (PFD) has vast application in reliability engineering and survival analysis. To identify and remove the unnatural variation in the process that follows PFD, we will develop control charts to control the process. PFD was introduced by Dallas [19] as the inverse of Pareto distribution. Meniconi et al. [20] showed it as a better fit for reliability data analysis over exponential, Weibull and lognormal distributions.

The core objective of our study is the construction of Shewhart, EWMA and HEWMA control chart by assuming that the distribution of the underlying process follows a Power function distribution. In next section, we have introduced Shewhart, EWMA and HEWMA under normality assumption. In Section 3, we have introduced PFD and provided the estimator of the shape parameter of the PFD. In Section 4, we have proposed the process monitoring for PFD. In Section 5, the steps involved in simulation studies are defined in detail. In Section 6, we have discussed the results obtained by using Section 5. In Section 7, concluding remarks on proposed control charts are given.

## 2 Some Existing Control Charts When the Assumption of Normality is Assumed

When the distribution of the process is normal, many types of control charts have been constructed in literature. Some of them are:

### 2.1 Shewhart [21] Control Chart

Suppose that the variable of interest has a normal distribution with mean  $\mu$  and variance  $\sigma^2$ , then control limits for the Shewhart chart is given by

$$LCL = \mu - (L * \sigma / \sqrt{n}) \quad \text{and} \quad UCL = \mu + (L * \sigma / \sqrt{n})$$

where “ $\sigma$ ” is the standard error of estimate and  $n$  is the sample size. Also, “ $L$ ” is coefficient which with a standard error of estimate determine in-control average run length.

### 2.2 Exponentially Weighted Moving Average (EWMA) Control Chart

Let the distribution of the underlying process having the sequence “ $Y_t$ ” is normal. Also, let the  $0 \leq \lambda_1 \leq 1$  is a known constant. Now EWMA statistics is given by

$$W_t = \lambda_2 y_t + (1 - \lambda_2) W_{t-1}.$$

The smoothing constant  $\lambda_2$  plays a very important here. As it approaches zero, it becomes sensitive for small and moderate shifts in mean and close to one. It approaches to Shewart control chart. The control limits for EWMA are given below:

$$UCL_{W_t} = \mu + L * \sqrt{V(W_t)}$$

$$LCL_{W_t} = \mu - L * \sqrt{V(W_t)}$$

**2.3 Hybrid Exponentially Weighted Moving Average (HEWMA) Control Chart**

Let the distribution of the underlying process having the sequence “ $Y_t$ ” is normal. Also, let the  $0 \leq \lambda_i \leq 1$  for  $i = 1, 2$  is a known constant. Now consider a new sequence HEW<sub>t</sub> as

$$HEW_t = \lambda_1 W_t + (1 - \lambda_1) HEW_{t-1} \tag{1}$$

where

$$W_t = \lambda_2 \hat{\mu}_t + (1 - \lambda_2) W_{t-1} \tag{2}$$

where HEW<sub>0</sub> = W<sub>0</sub> = μ and HEW<sub>t</sub> is a plotting statistics. By placing (2) in (1), we get the following:

$$HEW_t = \lambda_1 \lambda_2 \sum_{i=0}^{t-1} (1 - \lambda_1)^i \sum_{j=0}^{t-i-1} \left( \frac{1 - \lambda_1}{1 - \lambda_2} \right)^j Y_i + \lambda_1 \sum_{i=0}^{t-1} (1 - \lambda_1)^i (1 - \lambda_2)^{t-i} \mu + (1 - \lambda_1)^t \mu$$

The mean and variance of HEW<sub>t</sub> are given below:

$$E(HEW_t) = \mu$$

$$V(HEW_t) = \left( \frac{\lambda_1 \lambda_2}{(\lambda_1 - \lambda_2)} \right)^2 \left[ \sum_{i=1}^2 (1 - \lambda_1)^2 \left( 1 - (1 - \lambda_i)^{2t} / 1 - (1 - \lambda_i)^2 \right) - \frac{2(1 - \lambda_1)(1 - \lambda_2) \{ 1 - (1 - \lambda_1)^t (1 - \lambda_2)^t \}}{1 - (1 - \lambda_1)(1 - \lambda_2)} \right] \sigma^2$$

The control limits for the HEWMA control chart is explained as

$$UCL_{HEW_t} = \mu + L * \sqrt{V(HEW_t)}$$

$$LCL_{HEW_t} = \mu - L * \sqrt{V(HEW_t)}$$

**3 Power Function Distribution and Estimation of Its Shape Parameters**

The PFD is a flexible model for offering a suitable fit for the data related to the failure of components. Dallas [19] introduces it as an inverse of Pareto distribution. Further, Meniconi et al. [20] show that PFD is a better fit for the failure time data over Exponential, Lognormal and Weibull distribution.

The probability density function (pdf) and cumulative density function (cdf) for the PFD are given respectively by

$$f(y) = \frac{\gamma y^{\gamma-1}}{\beta^\gamma}; \quad 0 < y < \beta$$

and

$$F(y) = \left( \frac{y}{\beta} \right)^\gamma, \quad \text{where “}\beta\text{” and “}\gamma\text{” are the scale and shape parameters.}$$

Highly precise estimation of parameters for the distribution of a process is of immense importance as biased estimation may lead to misleading conclusions. In this section, our focus is

to estimate the parameters of a PFD using such an estimation method which is more simple and efficient to replace some existing comparatively complex and tedious estimation methods. Zaka et al. [22,23] have shown percentile estimator (P.E), maximum likelihood estimator (MLE), and modified maximum likelihood estimators (MMLE) are more efficient classical estimators for PFD.

### 3.1 Percentile Estimator (P.E) for the Shape Parameter of PFD

The percentile method is assumed to be first introduced by Dubey [24] for Weibull distribution to estimate the parameters of distribution and proved a better alternative to the MLE. Marks [25] and Zaka et al. [22] have extended the use of P.E to estimate the parameters of a different probability distribution. Zaka et al. [23] derived the P.E for the PFD and observed P.E as equally efficient as MLE, but the difference is the reduction in required constraints for estimating the unknown parameters. However, as the sample size is increased, both methods provide closer estimates of parameters of PFD. It is interesting to mention that P.E uses the two percentile points to estimate the parameters and no recursive equations are required to solve.

The P.E due to Zaka et al. [23] for the shape parameter ( $\gamma$ ) is given by

$$\hat{\gamma}_{P.E} = \frac{\ln\left(\frac{H}{L}\right)}{\ln\left(\frac{P_H}{P_L}\right)} \quad (3)$$

where “H” and “L” are the maximum and minimum percentile points, different pairs of H and L are used, as 25th, and 75th percentile, 10th and 90th percentile or any other pair of percentile can be used to calculate the shape parameter of PFD. We consider P.E as an unbiased estimator to construct the EWMA control chart. The variance of the “ $\hat{\gamma}_{P.E}$ ” is defined by

$$Var(\hat{\gamma}_{P.E}) = E(\hat{\gamma}_{P.E} - \gamma)^2 \quad (4)$$

### 3.2 MLE for the Shape Parameter of PFD

The MLE due to Zaka et al. [23] for the shape parameter “ $\gamma$ ” is given by

$$\hat{\gamma}_{MLE} = \left( \frac{n}{n \ln(\max(y_i)) - \sum_{i=1}^n \ln y_i} \right), \quad (5)$$

where  $\max(y_i)$  is the maximum observation in the data,  $\ln(y_i)$  is the natural logarithm of “ $y_i$ ” and “ $n$ ” is the sample size.

The variance of the  $\hat{\gamma}_{MLE}$  is given by

$$Var(\hat{\gamma}_{MLE}) = E(\hat{\gamma}_{MLE} - \gamma)^2. \quad (6)$$

### 3.3 MMLE for the Shape Parameter of PFD

Zaka et al. [23] proposed the MMLE for the shape parameter of the PFD. The MMLE due to the Zaka et al. [23] for the shape parameter ( $\gamma$ ) is given by

$$\hat{\gamma}_{MMLE} = -1 + \sqrt{1 + (\bar{y}^2/S^2)}, \quad (7)$$

where  $\bar{y}$  and  $S^2$  are the sample mean and sample variance, respectively.

The variance of the  $\hat{\gamma}_{MMLE}$  is given by

$$Var(\hat{\gamma}_{MMLE}) = E(\hat{\gamma}_{MMLE} - \gamma)^2. \quad (8)$$

#### 4 Proposed Process Monitoring For a Power Function Distribution

In the following section, P.E, MLE and MMLE due to Zaka et al. [23] are used to construct memory less and memory-based control charts to monitor the shape parameter of a process follows a PFD.

##### 4.1 Proposed Monitoring of Shape Parameter of PFD Using P.E

Let  $y_1, y_2, \dots, y_n$  be a sequence of independent and identical random variable generated from a process which follows a PFD with shape parameter “ $\gamma$ ”. It is important to note that we use the estimator of the shape parameter of the process instead of average of observations or single observations by assuming that  $E(\hat{\gamma}) = \gamma$ .

##### 4.1.1 Shewhart Type Control Chart Using P.E of PFD

The control limits for Shewhart-type control chart using P.E are given by

$$LCL_{\hat{\gamma}_{P.E}} = \gamma - L * \sqrt{var(\hat{\gamma}_{P.E})} \tag{9}$$

$$CL_{\hat{\gamma}_{P.E}} = \gamma \tag{10}$$

$$UCL_{\hat{\gamma}_{P.E}} = \gamma + L * \sqrt{var(\hat{\gamma}_{P.E})}. \tag{11}$$

##### 4.1.2 EWMA Control Chart Based on the P.E of PFD

We use the P.E of the shape parameter of the process instead of average of observations or single observations by assuming that  $E(\hat{\gamma}_{P.E}) = \gamma$ .

The EWMA statistic based on P.E of the PFD is given by

$$PEW_t = \lambda \hat{\gamma}_{P.E} + (1 - \lambda) PEW_{t-1}, \tag{12}$$

where  $\hat{\gamma}_{P.E}$  is a P.E as given by (1) for a PFD and  $PEW_{t-1}$  is the statistic on previous time. Also  $\lambda$  is a smoothing constant. The mean and variance are derived as

$$\text{For } t = 1 \text{ we get, } PEW_1 = \lambda \hat{\gamma}_{P.E(1)} + (1 - \lambda) PEW_0,$$

$$\text{For } t = 2 \text{ we get, } PEW_2 = \lambda \hat{\gamma}_{P.E(2)} + (1 - \lambda) PEW_1,$$

$$PEW_2 = \lambda \hat{\gamma}_{P.E(2)} + (1 - \lambda) \lambda \hat{\gamma}_{P.E(1)} + (1 - \lambda)^2 PEW_0.$$

Similarly, on generalizing, we get

$$PEW_t = \lambda \hat{\gamma}_{P.E(t)} + (1 - \lambda) \lambda \hat{\gamma}_{P.E(t-1)} + (1 - \lambda)^2 \hat{\gamma}_{P.E(t-2)} + \dots + (1 - \lambda)^{t-1} \lambda \hat{\gamma}_{P.E(1)} + (1 - \lambda)^t PEW_0, \tag{13}$$

where  $PEW_0 = \gamma$ , Taking expectation on, we get

$$E(PEW_t) = \lambda E(\hat{\gamma}_{P.E(t)}) + (1 - \lambda) \lambda E(\hat{\gamma}_{P.E(t-1)}) + \lambda (1 - \lambda)^2 E(\hat{\gamma}_{P.E(t-2)}) + \dots + \lambda (1 - \lambda)^{t-1} \lambda E(\hat{\gamma}_{P.E(1)}) + (1 - \lambda)^t PEW_0.$$

We have  $E(\hat{\gamma}_{P.E(t)}) = \gamma$ , and  $PEW_0 = \gamma$ , so the above may be written as

$$E(PEW_t) = \lambda \gamma + (1 - \lambda) \lambda \gamma + \lambda (1 - \lambda)^2 \gamma + \dots + \lambda (1 - \lambda)^{t-1} \lambda \gamma + (1 - \lambda)^t \gamma,$$

$$E(PEW_t) = \gamma \left[ \lambda \left\{ 1 + (1 - \lambda) + (1 - \lambda)^2 + \dots + (1 - \lambda)^{t-1} \right\} + (1 - \lambda)^t \right].$$

After solving the geometric series, we get

$$E(PEW_t) = \gamma \left[ \lambda \left[ \frac{1 - (1 - \lambda)^t}{1 - (1 - \lambda)} \right] + (1 - \lambda)^t \right],$$

Finally, we get

$$E(PEW_t) = \gamma. \quad (14)$$

To get the variance, apply variance on the

$$\begin{aligned} Var(PEW_t) &= \lambda Var(\hat{\gamma}_{P.E(t)}) + (1 - \lambda) \lambda Var(\hat{\gamma}_{P.E(t-1)}) + \lambda (1 - \lambda)^2 Var(\hat{\gamma}_{P.E(t-2)}) + \dots \\ &\quad + \lambda (1 - \lambda)^{t-1} \lambda Var(\hat{\gamma}_{P.E(1)}) + (1 - \lambda)^t PEW_0. \end{aligned}$$

Let  $Var(\hat{\gamma}_{P.E(t)}) = v = E(\hat{\gamma}_{P.E} - \gamma)^2$ , we get

$$Var(PEW_t) = \lambda^2 v \left( 1 + (1 - \lambda)^2 + (1 - \lambda)^4 + \dots + (1 - \lambda)^{2(t-1)} \right).$$

After simplification of a geometric series, we get

$$Var(PEW_t) = \lambda^2 v \left( \frac{1 - (1 - \lambda)^{2t}}{1 - (1 - \lambda)^2} \right).$$

Alternatively, we get

$$Var(PEW_t) = v \left( 1 - (1 - \lambda)^{2t} \right) \left( \frac{\lambda}{2 - \lambda} \right). \quad (15)$$

Hence the control limits of an EWMA based on P.E are given by

$$LCL_{PEW_t} = \gamma - L * \sqrt{var(\hat{\gamma}_{P.E}) * \frac{\lambda}{(2 - \lambda)} \left( 1 - (1 - \lambda)^{2t} \right)}$$

$$CL_{PEW_t} = \gamma$$

$$UCL_{PEW_t} = \gamma + L * \sqrt{var(\hat{\gamma}_{P.E}) * \frac{\lambda}{(2 - \lambda)} \left( 1 - (1 - \lambda)^{2t} \right)}.$$

where  $1 - (1 - \lambda)^{2t}$  approaches to unity as “ $t$ ” get large so after ignoring it, the control limits for EWMA takes the form as given by

$$LCL_{PEW_t} = \gamma - L * \sqrt{var(\hat{\gamma}_{P.E}) * \frac{\lambda}{(2 - \lambda)}} \quad (16)$$

$$CL_{PEW_t} = \gamma \quad (17)$$

$$UCL_{PEW_t} = \gamma + L * \sqrt{\text{var}(\hat{\gamma}_{P.E}) * \frac{\lambda}{(2-\lambda)}}. \tag{18}$$

**4.1.3 HEWMA Control Chart Based on P.E of the Shape Parameter of PFD**

The HEWMA statistic using P.E of the shape parameter of the PFD is stated by

$$PHEW_t = \lambda_1 PEW_t + (1 - \lambda_1) PHEW_{t-1} \tag{19}$$

where  $PEW_t$  is a usual EWMA statistic based on P.E given as

$$PEW_t = \lambda_2 \hat{\gamma}_{P.E} + (1 - \lambda_2) PEW_{t-1} \tag{20}$$

and  $PHEW_{t-1}$  is the statistics on previous time. Also  $\lambda_1$  and  $\lambda_2$  are smoothing constant here. The control limits are given for HEMMA control chart using P.E for the shape parameter of the PFD and using (13) we get

$$\begin{aligned} PHEW_t = & \lambda_1 \left( \lambda_2 \hat{\gamma}_{P.E} + (1 - \lambda_2) \sum_{j=0}^1 \left( \frac{(1 - \lambda_1)}{(1 - \lambda_2)} \right)^j \hat{\gamma}_{P.E(t-1)} + (1 - \lambda_2)^2 \sum_{j=0}^2 \left( \frac{(1 - \lambda_1)}{(1 - \lambda_2)} \right)^j \hat{\gamma}_{P.E(t-2)} \right. \\ & + (1 - \lambda_2)^3 \sum_{j=0}^3 \left( \frac{(1 - \lambda_1)}{(1 - \lambda_2)} \right)^j \hat{\gamma}_{P.E(t-3)} + \dots + (1 - \lambda_2)^{t-1} \sum_{j=0}^{t-1} \left( \frac{(1 - \lambda_1)}{(1 - \lambda_2)} \right)^j \hat{\gamma}_{P.E(1)} \\ & \left. + \lambda_1 (1 - \lambda_2)^t \sum_{j=0}^t \left( \frac{(1 - \lambda_1)}{(1 - \lambda_2)} \right)^j \hat{\gamma}_{P.E(0)} + (1 - \lambda_2)^t PHE_t \right) \end{aligned}$$

$$LCL_{PHEW_t}$$

$$= \gamma - L$$

$$* \frac{\lambda_1 \lambda_2}{(\lambda_1 - \lambda_2)} \sqrt{\left( \sum_{i=1}^2 \frac{(1 - \lambda_i)^2 (1 - (1 - \lambda_i)^{2t})}{1 - (1 - \lambda_i)^2} - \frac{2(1 - \lambda_1)(1 - \lambda_2) \{1 - (1 - \lambda_1)^t (1 - \lambda_2)^t\}}{1 - (1 - \lambda_1)(1 - \lambda_2)} \right) \text{var}(\hat{\gamma}_{P.E})}$$

$$CL_{PHEW_t} = \gamma$$

$$UCL_{PHEW_t}$$

$$= \gamma + L$$

$$* \frac{\lambda_1 \lambda_2}{(\lambda_1 - \lambda_2)} \sqrt{\left( \sum_{i=1}^2 \frac{(1 - \lambda_i)^2 (1 - (1 - \lambda_i)^{2t})}{1 - (1 - \lambda_i)^2} - \frac{2(1 - \lambda_1)(1 - \lambda_2) \{1 - (1 - \lambda_1)^t (1 - \lambda_2)^t\}}{1 - (1 - \lambda_1)(1 - \lambda_2)} \right) \text{var}(\hat{\gamma}_{P.E})}$$

**4.2 Proposed Monitoring of the Shape Parameter of PFD Using MLE**

Let  $y_1, y_2, \dots, y_n$  be a sequence of independent and identical random variable generated from a process which follows a PFD with shape parameter “ $\gamma$ ”. It is important to note that we use the estimator of shape parameter of the process instead of average of observations or single observations by assuming that  $E(\hat{\gamma}) = \gamma$ .

#### 4.2.1 Shewhart-Type Control Chart for MLE of PFD

The control limits for Shewhart-type control charts under MLE may be given as

$$LCL_{\hat{\gamma}_{MLE}} = \gamma - L * \sqrt{\text{var}(\hat{\gamma}_{MLE})} \quad (21)$$

$$CL_{\hat{\gamma}_{MLE}} = \gamma \quad (22)$$

$$UCL_{\hat{\gamma}_{MLE}} = \gamma + L * \sqrt{\text{var}(\hat{\gamma}_{MLE})} \quad (23)$$

#### 4.2.2 EWMA Control Chart for the MLE of PFD

The EWMA statistic by using MLE of PFD may be written as

$$PEW_t = \lambda_2 \hat{\gamma}_{MLE} + (1 - \lambda_2) PEW_{t-1}$$

where  $\hat{\gamma}_{MLE}$  is MLE for PFD and  $PEW_{t-1}$  is the statistic on previous time. Also  $\lambda_2$  is smoothing constant. Using the mean and variance for the EWMA statistics given in (14) and (15). The control limits given below may be obtained PFD as shown below:

$$LCL_{PEW_t} = \gamma - L * \sqrt{\text{Var}(\hat{\gamma}_{MLE}) \left( \frac{\lambda}{2 - \lambda} \right)} \quad (24)$$

$$CL_{PEW_t} = \gamma \quad (25)$$

$$UCL_{PEW_t} = \gamma + L * \sqrt{\text{Var}(\hat{\gamma}_{MLE}) \left( \frac{\lambda}{2 - \lambda} \right)} \quad (26)$$

#### 4.2.3 HEWMA Control Chart for the MLE of the PFD

The HEWMA statistic by using MLE of PFD may be written as

$$PHEW_t = \lambda_1 PEW_t + (1 - \lambda_1) PHEW_{t-1} \quad (27)$$

where  $PEW_t$  is a usual EWMA statistic given as

$$PEW_t = \lambda \hat{\gamma}_{MLE} + (1 - \lambda) PEW_{t-1} \quad (28)$$

where  $\hat{\gamma}_{MLE}$  is maximum likelihood estimator for PFD and  $PEW_{t-1}$  is the statistic on previous time. Also  $\lambda$  is smoothing constant, we get the control limits for HEMMA as

$$\begin{aligned} LCL_{PHEW_t} &= \gamma - L \\ &* \frac{\lambda_1 \lambda_2}{(\lambda_1 - \lambda_2)} \sqrt{\left( \sum_{i=1}^2 \frac{(1 - \lambda_i)^2 (1 - (1 - \lambda_i)^{2t})}{1 - (1 - \lambda_i)^2} - \frac{2(1 - \lambda_1)(1 - \lambda_2) \{1 - (1 - \lambda_1)^t (1 - \lambda_2)^t\}}{1 - (1 - \lambda_1)(1 - \lambda_2)} \right) * \text{Var}(\hat{\gamma}_{MLE})} \end{aligned}$$

$$CL_{PHEW_t} = \gamma$$



$$UCL_{PHEW_t}$$

$$= \gamma + L$$

$$* \frac{\lambda_1 \lambda_2}{(\lambda_1 - \lambda_2)} \sqrt{\left( \sum_{i=1}^2 \frac{(1 - \lambda_i)^2 (1 - (1 - \lambda_i)^{2t})}{1 - (1 - \lambda_i)^2} - \frac{2(1 - \lambda_1)(1 - \lambda_2) \{1 - (1 - \lambda_1)^t (1 - \lambda_2)^t\}}{1 - (1 - \lambda_1)(1 - \lambda_2)} \right) * Var(\hat{\gamma}_{MLE})}$$

### 4.3 Proposed Monitoring of the Shape Parameter of PFD Using MMLE

Let  $y_1, y_2, \dots, y_n$  be a sequence of independent and identical random variable generated from a process which follows a PFD with shape parameter “ $\gamma$ ”. It is important to note that we use the estimator of shape parameter of the process instead of average of observations or single observations by assuming that  $E(\hat{\gamma}) = \gamma$ .

#### 4.3.1 Shewhart-Type Control Chart for MMLE of PFD

The control limits for Shewhart control charts under modified maximum likelihood estimator may be given as

$$LCL_{\hat{\gamma}_{MMLE}} = \gamma - (L * \sqrt{Var(\hat{\gamma}_{MMLE})}) \tag{29}$$

$$CL_{\hat{\gamma}_{MMLE}} = \gamma \tag{30}$$

$$UCL_{\hat{\gamma}_{MMLE}} = \gamma + (L * \sqrt{Var(\hat{\gamma}_{MMLE})}) \tag{31}$$

#### 4.3.2 EWMA Control Chart for the MMLE of PFD

The EWMA statistic by using MMLE of PFD may be written as

$$PEW_t = \lambda_2 \hat{\gamma}_{MMLE} + (1 - \lambda_2) PEW_{t-1} \tag{32}$$

where  $\hat{\gamma}_{MMLE}$  is MMLE for PFD and  $PEW_{t-1}$  is the statistic on previous time. Also  $\lambda_2$  is smoothing constant. By using the mean and variance for the EWMA statistics given in (14) and (15), the control limits given below may be obtained PFD as given below:

$$LCL_{PEW_t} = \gamma - L * \sqrt{Var(\hat{\gamma}_{MMLE}) \left( \frac{\lambda}{2 - \lambda} \right)} \tag{33}$$

$$CL_{PEW_t} = \gamma \tag{34}$$

$$UCL_{PEW_t} = \gamma + L * \sqrt{Var(\hat{\gamma}_{MMLE}) \left( \frac{\lambda}{2 - \lambda} \right)} \tag{35}$$

#### 4.3.3 HEWMA Control Chart for the MMLE of the PFD

The HEWMA statistic by using MMLE of PFD may be written as

$$PHEW_t = \lambda_1 PEW_t + (1 - \lambda_1) PHEW_{t-1}$$

where  $PEW_t$  is a usual EWMA statistic given as

$$PEW_t = \lambda_2 \hat{\gamma}_{MMLE} + (1 - \lambda_2) PEW_{t-1}$$

where  $\hat{\gamma}_{MLE}$  is maximum likelihood estimator for PFD and  $PEW_{t-1}$  is the statistic on previous time. Also,  $\lambda$  is smoothing constant; we may get the control limits for HEMMA as

$$LCL_{PHEW_t}$$

$$= \gamma - L$$

$$* \frac{\lambda_1 \lambda_2}{(\lambda_1 - \lambda_2)} \sqrt{\left( \sum_{i=1}^2 \frac{(1 - \lambda_i)^2 (1 - (1 - \lambda_i)^{2t})}{1 - (1 - \lambda_i)^2} - \frac{2(1 - \lambda_1)(1 - \lambda_2) \{1 - (1 - \lambda_1)^t (1 - \lambda_2)^t\}}{1 - (1 - \lambda_1)(1 - \lambda_2)} \right) * Var(\hat{\gamma}_{MMLE})}$$

$$CL_{PHEW_t} = \gamma$$

$$UCL_{PHEW_t}$$

$$= \gamma + L$$

$$* \frac{\lambda_1 \lambda_2}{(\lambda_1 - \lambda_2)} \sqrt{\left( \sum_{i=1}^2 \frac{(1 - \lambda_i)^2 (1 - (1 - \lambda_i)^{2t})}{1 - (1 - \lambda_i)^2} - \frac{2(1 - \lambda_1)(1 - \lambda_2) \{1 - (1 - \lambda_1)^t (1 - \lambda_2)^t\}}{1 - (1 - \lambda_1)(1 - \lambda_2)} \right) * Var(\hat{\gamma}_{MMLE})}$$

## 5 Simulation Study

To compare the performance of Shewhart-type, EWMA and HEWMA control charts for monitoring the shape parameter of the PFD, we use the simulation approach to generate Average Run Length (ARL). We use the following algorithm for simulation.

The Monte Carlo Simulation program for the proposed control charts is executed assuming a process is following PFD.

1. Generate a random sample of size  $n = 150$  on  $Y_t$  from the PFD with parameters  $(\beta, \gamma) = (1, 2)$ .
2. Compute  $\hat{\gamma}_{*t}$  where  $*$  = P.E, MLE and MMLE, using (3), (5) and (7).
3. Repeat Steps 1 and 2 for 5000 times and compute  $E(\hat{\gamma}_{*t})$  and  $V(\hat{\gamma}_{*t})$ .
4. Repeat Step 3 for 5000 times and compute the mean of  $E(\hat{\gamma}_{*t})$  and  $V(\hat{\gamma}_{*t})$ .
5. Compute control limits to construct Shewhart-type control chart based on  $\hat{\gamma}_{*t}$ .
6. Compute ARL value for each Shewhart-type control chart that based on  $\hat{\gamma}_{*t}$  given that process is an in-control state.
7. Now fix  $ARL_0 = 350$  for the in-control state of the process and search the suitable value of "L" so that  $ARL_0$  for the in-control state of a process is achieved.
8. Now assume if the process parameter  $\gamma$  is shifted by 0.05 from its true value and compute  $ARL_1$ . This step is repeated for different shift values 0.10, 0.15, 0.25 & 0.50, and compute  $ARL_1$  in each case of shift values.
9. Plot ARL values against the values of shift that used in Steps 7 & 8.
10. It is to note that the procedure of Shewhart-type control chart based on  $\hat{\gamma}_{*t}$  observe whether the process following the PFD is in-control or out of control. If the process is in-control, go to Step 1. Otherwise, record the Run Length, i.e., the process remained in control before being declared out-of-control.
11. Repeat this process 5000 times to obtain the ARLs, SDRLs and fractiles.

### 5.1 Computing Control Chart Based on EWMA Statistics Integrated with P.E, MLE and MMLE, $PEW_{*t}$ for PFD

12. Repeat Steps 1 and 2 to compute EWMA statistics,  $PEW_{*t}$  taking  $\lambda = 0.6$  and  $PEW_{*0}$  as the target value of the parameter.
13. Repeat Steps 3 and 4 for 5000 times to compute the mean of  $E(PEW_{*t})$  and  $V(PEW_{*t})$ .
14. Compute control limits for EWMA control charts integrated with  $PEW_{*t}$  statistics subject to the process with PFD is an in-control state.
15. Repeat from Steps 6 to 11.

### 5.2 Computing Control Chart Based on HEWMA Statistics Integrated with P.E, MLE and MMLE, $PHEW_{*t}$ for PFD

16. Repeat Steps 1 and 2 to compute HEWMA statistics,  $HPEW_{*t}$  taking  $\lambda_1 = 0.30$ ,  $\lambda_2 = 0.10$ , and  $HPEW_{*0}$  as the target value of the parameter.
17. Repeat Steps 3 and 4 for 5000 times to compute the mean of  $E(PHEW_{*t})$  and  $V(PHEW_{*t})$ .
18. Compute control limits for HEWMA control charts integrated with  $HPEW_{*t}$  statistics subject to the process with PFD is an in-control state.
19. Repeat from Steps 6 to 11.
20. Assume  $\lambda_1 = 0.30$ ,  $\lambda_2 = 0.50$  and repeat from Steps 17 to 19.
21. Assume  $\lambda_1 = 0.30$ ,  $\lambda_2 = 0.75$ , and repeat from Steps 17 to 19.

## 6 Results and Discussion

Average Run length is considered for comparison in between the control charts based on MLE, MMLE and P.E. The timely detection of an outlier in the process is preferred. So the control chart having a minimum ARL value is considered to be good.

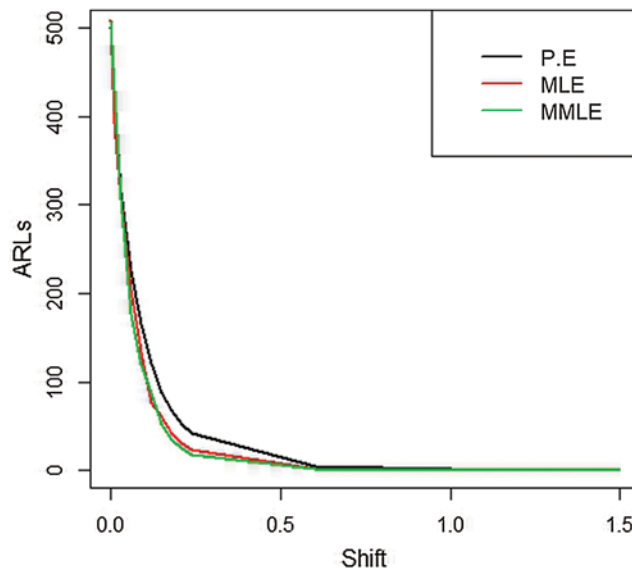
We have constructed three control charts, i.e., Shewhart control chart based on P.E, Shewhart control chart based on MLE and Shewhart control chart based on MMLE. We compare these control charts by using the above mentioned simulation steps. We have presented the ARLs by setting the  $ARL_0 = 500$ .

We observe from [Tab. 1](#) and [Fig. 1](#) that the performance of a Shewhart control chart based on MLE is better than P.E and MMLE. We see that the MLE early detects the shift in the process. For instance the control chart based on the estimate of shape parameter using P.E gives  $ARL_1$ , i.e., out of control average run length as 419.257 when there is shift of 0.01 in the shape parameter PFD but MLE gives  $ARL_1 = 392.25$  and MMLE gives  $ARL_1 = 430.103$ . So, MLE is more efficient to detect the small shift in the process compared to P.E and MMLE if the underlying distribution of the process is PFD.

We observe from [Tab. 2](#) and [Fig. 2](#) that for  $\lambda = 0.10$ , MLE performs better as compare to P.E and MMLE. We take a shift of 0.01 in the shape parameter of PFD and see that control charts under P.E provide  $ARL_1 = 356.138$ , control charts under MLE gives  $ARL_1 = 287.2285$  and control charts under MMLE gives  $ARL_1 = 307.261$ . We see that a control chart under MLE is better than control charts under P.E and MMLE. We take different shifts and observe the same behaviour. We observe that the  $ARL_1$  reduces to 1 more efficiently when we use EWMA control chart under MLE as compare to the control chart under P.E and control chart under MMLE.

**Table 1:** Shewhart control chart based on P.E, MLE and MMLE

Estimation methods		Shift												
		0	0.01	0.03	0.06	0.09	0.120	0.150	0.180	0.210	0.240	0.60	1.00	1.5
P.E	ARL	500.112	419.257	315.537	226.168	166.375	120.781	88.468	67.769	51.955	42.142	4.435	1.531	1.044
	SDRL	494.452	400.9711	323.4627	234.0356	169.7425	123.102	87.3128	62.744	50.452	41.849	3.888	0.9294	0.210
	P10	51.0	44.9	33.9	22.9	19.00	14.9	10.0	7.90	5	5	1	1	1
	P25	145	111.0	94.0	67.0	54.00	39.0	27	20	16	14	2	1	1
	P50	348	262.5	216.0	160.0	113.00	81.5	64	52	38	30	3	1	1
	P75	699	535.5	422.5	304.5	220.25	161.0	121	97.25	72	58	6	2	1
MLE	P90	1179.5	919.4	752.0	513.1	374.50	277.1	190.2	151.2	112	91	10	3	1
	ARL	500.632	392.25	305.756	203.81	134.122	76.206	60.765	42.138	30.57	23.202	2.195	1.066	1.001
	SDRL	513.118	410.527	323.470	202.934	133.331	85.404	59.098	39.925	30.320	21.956	1.571	0.2715	0.031
	P10	59.00	41.00	30.90	19.0	13.90	9.00	7	5	4	3	1	1	1
	P25	150	121.00	86.00	58.0	41.00	27.00	18	13	9	7	1	1	1
	P50	341	296.50	211.00	140.0	93.00	65.00	43	30	21	16	2	1	1
MMLE	P75	713.75	603.25	436.25	280.0	186.25	123.25	85	61	41	33	3	1	1
	P90	1188.1	940.10	685.00	472.6	290.10	202.00	134	93	68	53	4	1	1
	ARL	500.937	430.103	306.829	177.613	120.375	88.708	52.426	35.17	24.919	17.74	1.698	1.031	1
	SDRL	507.6469	435.8804	299.7871	187.2064	118.554	78.553	54.38719	34.2362	24.7146	17.105	1.1198	0.1845	0
	P10	53.00	43.90	33.00	20	14.00	8	5.0	4.0	3	2	1	1	1
	P25	145.75	121.75	94	48	34.75	22	16	11	8	6	1	1	1
MMLE	P50	350.50	303.50	215	123	81	54	35.5	24	18	13	1	1	1
	P75	706.25	572.75	425	247	166	100	73	49	33	24	2	1	1
	P90	1194.3	1016.40	691	410	287.5	176	116.1	79.2	58	41	3	1	1

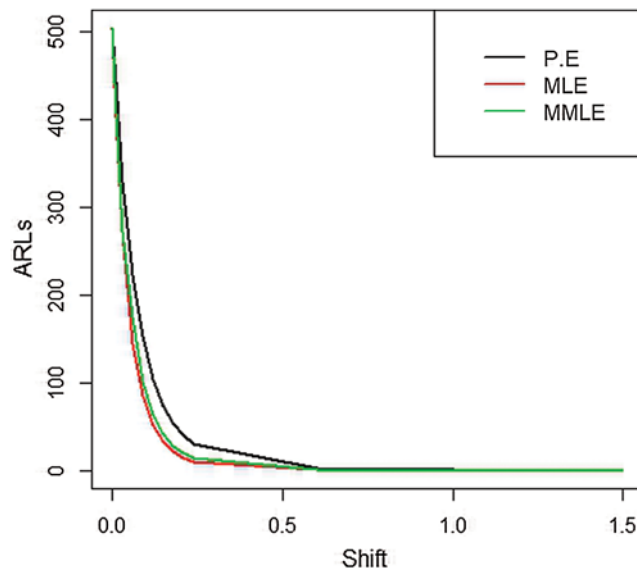


**Figure 1:** ARLs for the shape parameter of PFD under Shewhart control chart

From [Tab. 3](#) and [Fig. 3](#), it is clear that for  $\lambda = 0.60$ , at shift = 0.01, P.E provides  $ARL_1 = 435.08$ , control charts under MLE give  $ARL_1 = 394.365$  and control charts under MMLE gives  $ARL_1 = 396.261$ . We conclude that a control chart under MLE is better than control charts under P.E and MMLE. We also see that if we use different shifts for shape parameter, EWMA under MLE detects early any shift to shape parameter as compare to EWMA under P.E and MMLE.

**Table 2:** EWMA control chart when  $\lambda = 0.10$  based on P.E, MLE and MMLE for power function distribution

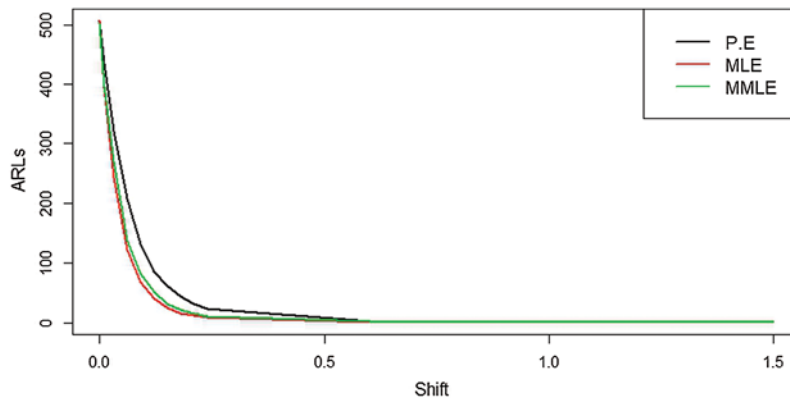
Estimation methods		Shift												
		0	0.01	0.03	0.06	0.09	0.120	0.150	0.180	0.210	0.240	0.60	1.00	1.5
P.E L = 4.20	ARL	500.748	356.138	183.057	84.354	47.99	32.016	23.563	17.803	14.64	12.441	4.372	2.73	1.977
	SDRL	478.0	336.079	170.97	71.70	35.307	21.079	13.869	9.248	6.7318	5.3947	1.223	0.662	0.3776
	P10	64.0	48.00	32.00	19	15.0	12	10	8	7.9	7	3	2	2
	P25	162.0	110.00	62.75	34	23	17	14	11	10	8	4	2	2
	P50	368.0	254.00	125.00	62	38	26	20	15	13	11	4	3	2
	P75	677.0	493.25	247.00	112	62	41	30	22	18	15	5	3	2
	P90	1107.1	786.30	410.6	180	97.1	59	42	31	23	19	6	3	2
MLE L = 4.200	ARL	500.401	299.469	124.776	47.721	26.853	17.838	13.24	10.548	8.742	7.46	5.882	1.979	1.404
	SDRL	485.173	287.2285	105.3997	34.2788	16.0943	8.92667	5.631173	4.001	2.984685	2.4042	0.6689	0.3265	0.490
	P10	73.9	44.0	27.0	16	11	9	7.0	6	5	5	2	2	1
	P25	165.0	94.0	48.0	23	16	12	9.0	8	6	6	3	2	1
	P50	338.0	205.0	97.0	38	23	16	12.0	10	8	7	3	2	1
	P75	691.0	390.5	169.0	63	34	22	16.0	13	11	9	3	2	2
	P90	1187.8	665.0	255.1	93	47	30	20.1	16	13	11	4	2	2
MMLE L = 4.03	ARL	500.466	307.261	131.812	51.461	29.368	18.964	14.105	11.147	9.021	7.704	2.994	1.947	1.376
	SDRL	501.4857	303.2855	115.9346	38.27858	19.01347	11.151	7.079	5.025	3.607	2.805	0.758	0.4175	0.484
	P10	69.00	48.9	27.00	15	11	8	7	6	5	5	2	1	1
	P25	158.75	100	49	24	16	11	9	8	6	6	3	2	1
	P50	356.5	211	97	40	24	16	13	10	8	7	3	2	1
	P75	654.00	406	172.25	68	38	23	18	14	11	9	3	2	2
	P90	1193.1	688.3	282.10	105	54	33	23	17	14	11	4	2	2



**Figure 2:** ARLs for the shape parameter of PFD under EWMA control chart at  $\lambda = 0.75$

**Table 3:** EWMA control chart when  $\lambda = 0.60$  based on P.E, MLE and MMLE for power function distribution

Estimation methods		Shift												
		0	0.01	0.03	0.06	0.09	0.120	0.150	0.180	0.210	0.240	0.60	1.00	1.5
P.E L = 4.15	ARL	500.137	435.08	321.381	207.639	133.081	86.096	61.456	43.542	31.896	23.98	3.243	1.54	1.079
	SDRL	492.2264	422.12	328.01	211.47	132.1367	85.615	58.602	41.924	30.98	23.15	2.015	0.674	0.269
	P10	54.90	51.00	34.90	22.00	13.00	10.0	8.0	6.0	5	4	1	1	1
	P25	141.00	118.75	92.75	62	38	25	19	14	11	8	2	1	1
	P50	341.00	302.5	225.00	142	94	61	46	31	23	16	3	1	1
	P75	726.75	623	427.25	279.25	183.25	118	86	59	43	32	4	2	1
	P90	1211.20	1019.5	736.10	484.60	300.10	195.1	135.1	94.1	68	53	6	2	1
MLE L = 4.16	ARL	500.937	394.365	242.607	123.358	68.048	41.33	24.3	16.131	11.529	8.253	1.66	1.057	1.055
	SDRL	517.3019	406.1537	236.597	119.5382	68.0906	39.141	23.260	14.578	9.871	6.7942	0.739	0.2319	1
	P10	56.0	42.00	29.00	16.00	9.00	6.00	4.00	3.0	3	2	1	1	0
	P25	151.5	116.75	73.75	38.00	22.00	14.75	8.00	6.0	4	4	1	1	1
	P50	340.0	273.00	175.00	86.00	48.00	29.50	17.00	12.0	9	6	2	1	1
	P75	660.5	523.00	334.00	173.25	90.25	57.00	31.25	21.0	15	11	2	1	1
	P90	1185.2	921.30	547.00	280.20	149.30	91.10	54.00	34.1	25	17	3	1	1
MMLE L = 4.34	ARL	500.2	396.518	270.38	139.086	83.52	51.653	32.266	21.861	15.213	11.323	1.875	1.109	1
	SDRL	54.0	405.9102	282.9092	138.3694	85.027	49.803	32.612	21.058	14.529	9.906	0.9155	0.311	0
	P10	140.5	38.00	23.90	15.00	9.00	7.0	5	4	3	3	1	1	1
	P25	240.0	100.00	78.75	38	26	17.0	11	7	6	5	1	1	1
	P50	560.5	266.00	186	98.50	58	37.0	21	15	11	8	2	1	1
	P75	1085.2	539.25	366.25	189.25	111.25	70.0	41	30	19	15	2	1	1
	P90	56.0	956.00	621.10	323.0	191.10	117.1	74	48	33	23	3	2	1



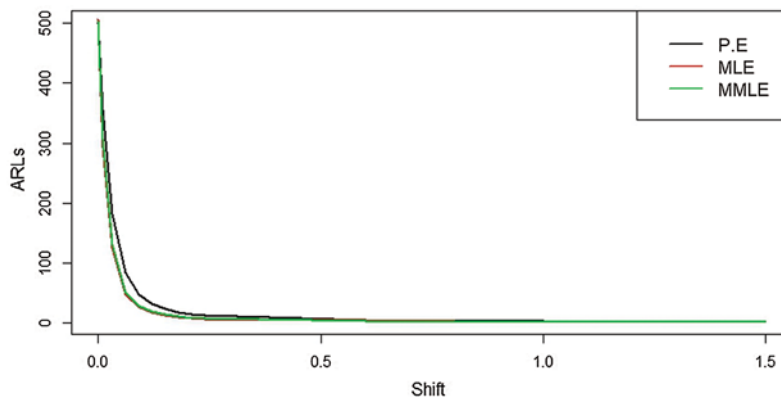
**Figure 3:** ARLs for the shape parameter of PFD under EWMA control chart at  $\lambda = 0.60$

We can see in Tab. 4 and Fig. 4 that when  $\lambda = 0.75$ , by using shift = 0.01, EWMA control charts under P.E provide  $ARL_1 = 444.335$ , control charts under MLE gives  $ARL_1 = 403.633$  and control charts under MMLE gives  $ARL_1 = 407.456$ . We conclude that EWMA control chart under MLE is better than the control charts under P.E and MMLE.

We also observe from Tabs. 1–4 that with an increase in the value of  $\lambda$ , the EWMA control charts behave like Shewhart control chart showing an increase in  $ARL_1$ . So EWMA performs better than Shewhart control chart for all three control charts based on P.E, MLE and MMLE.

**Table 4:** EWMA control chart when  $\lambda = 0.75$  based on P.E, MLE and MMLE for power function distribution

Estimation methods		Shift												
		0	0.01	0.03	0.06	0.09	0.120	0.150	0.180	0.210	0.240	0.60	1.00	1.5
P.E L = 4.175	ARL	500.663	444.335	330.098	224.091	154.421	105.199	75.218	54.583	40.976	31.366	3.643	1.528	1.064
	SDRL	484.7689	432.3127	319.7975	232.1184	156.9695	104.374	70.949	51.22	39.12	30.53	2.71	0.753	0.248
	P10	55.90	51.9	38.0	22.0	15.9	11.9	9	6.00	5.0	5	1	1	1
	P25	141.75	127.0	95.0	62.0	45	30	22	17	13	10	2	1	1
	P50	341.50	312.5	231.0	156.5	105	75	56	42	29	22	3	1	1
	P75	707.50	627.0	459.0	306.5	209	147	105	76.25	58	43	5	2	1
MLE L = 4.186	ARL	500.5	403.633	273.554	145.231	85.901	52.745	34.187	21.88	15.408	10.93	1.625	1.037	1
	SDRL	485.9248	395.9084	274.9435	140.1837	85.61952	51.208	33.85111	20.62608	14.71401	9.588	0.830	0.188	0
	P10	55.90	42.00	30.0	16.0	10.0	7	5.0	3	3.0	2	1	1	1
	P25	152.75	123.75	75	42	24	17	11	7	5	4	1	1	1
	P50	344.50	298	190.5	101	58.5	37	23.5	16	11	8	1	1	1
	P75	697.00	540.5	376.5	197	119	74	46	29	21	15	2	1	1
MMLE L = 4.3805	ARL	500.451	407.456	273.466	175.28	102.127	64.157	41.97	28.546	20.36	14.634	1.905	1.104	1
	SDRL	495.18	393.7306	277.9532	182.0611	96.39647	62.7544	40.03821	26.91826	18.409	13.255	1.0251	0.327	0
	P10	58.00	47.8	26.0	21.0	11.0	7	6	4.00	3	3	1	1	1
	P25	155.75	128.0	79.0	49.0	29.0	19	13	9	7	5	1	1	1
	P50	353.00	308.0	188.0	120.5	74.5	44	29	20	14	11	2	1	1
	P75	702.50	542.5	369.5	241.0	146.0	92	58	38.25	29	20	2	1	1
	P90	1109.00	921.1	615.0	402.1	243.0	147	94	66	47	311	3	1	1

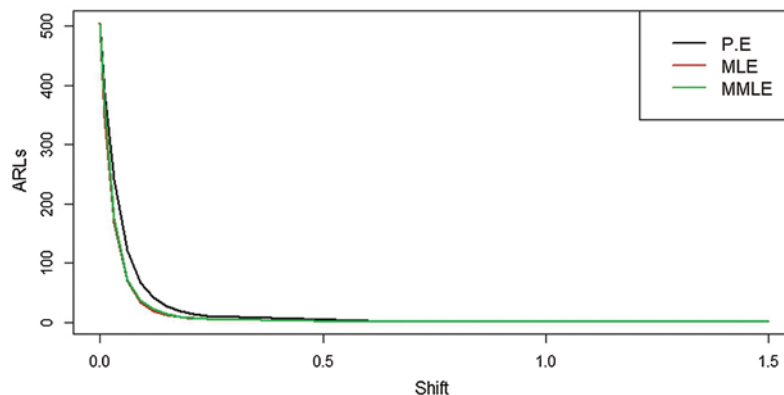


**Figure 4:** ARLs for the shape parameter of PFD under EWMA control chart at  $\lambda = 0.10$

We have developed HEWMA control chart based on P.E, MLE and MMLE when  $\lambda_1 = 0.30$  and  $\lambda_2 = 0.10$  in [Tab. 5](#) and [Fig. 5](#). We can see from [Tab. 5](#) that MLE performs better as compare to control charts based on P.E and MMLE when the underlying distribution of the process is PFD. We see that for a shift of 0.01 in the shape parameter of an underlying process, the control chart based on P.E gives  $ARL_1 = 328.82$ , the control chart based on MLE provide  $ARL_1 = 297.866$  and the control chart based on MMLE detects the shift at  $ARL_1 = 311.973$ . By further analysis of the results given in [Tab. 5](#), we observe the same behaviour of HEWMA under MLE as it gives smaller  $ARL_1$  as compare to HEWMA under P.E and MMLE.

**Table 5:** HEWMA control chart when  $\lambda_1 = 0.30$ ,  $\lambda_2 = 0.10$  based on P.E, MLE and MMLE for power function distribution

Estimation methods		Shift												
		0	0.01	0.03	0.06	0.09	0.120	0.150	0.180	0.210	0.240	0.60	1.00	1.5
P.E L = 4.065	ARL	500.661	328.82	171.46	68.485	38.939	23.809	17.697	13.63	11.722	10.049	3.977	2.443	1.748
	SDRL	922.781	638.93	298.782	108.08	50.85654	28.718	18.531	12.675	9.607	7.349	1.3705	0.6443	0.478
	P10	1.0	1.0	1.00	1.00	1.0	1.0	1	1	1	1	2	2	1
	P25	1	1	1	1	1	1	1	1	1	4	3	2	1
	P50	1	1	1	15.5	20	16	15	12	11	10	4	2	2
	P75	654.5	415	226.25	96.25	58	36	26	21	17	14	5	3	2
MLE L = 4.30	P90	1785.8	1039.5	574.5	204	108.1	61.1	43	29	24	19	6	3	2
	ARL	500.43	297.866	115.949	39.929	21.219	15.007	11.127	8.648	6.634	5.548	1.529	1.048	1.154
	SDRL	563.635	574.133	189.941	51.6193	22.1502	12.625	7.9184	5.592251	4.1392	3.223815	0.7097	0.4200	0.36
	P10	1.0	1.0	1.00	1	1	1	1	1	1	1.00	2	1	1
	P25	1.0	1.0	1.00	1	1	1	5	6	5	5.00	2	2	1
	P50	1.0	1.0	13.00	23	17	14	11	9	8	7.00	3	2	1
MMLE L = 4.30	P75	224.0	381.5	161.25	61	32	22	16	12	10	8.25	3	2	1
	P90	245	301.10	115.949	39.929	21.219	15.007	11.127	9	7.764	6.597	2.697	1.819	1.154
	ARL	500.62	311.973	117.135	45.747	25.107	15.898	11.513	9	7.764	6.597	2.697	1.819	1
	SDRL	504.1815	284.9462	106.4273	36.10785	18.01733	10.273	7.019	5.069	3.815	3.129	0.712	0.213	0
	P10	67.90	43.90	21.00	11	7	5	4	3	2	2	1	1	1
	P25	156.75	96	43	20	12	9	6	5	4	3	1	1	1
MMLE L = 4.30	P50	345.50	206	86.50	37	21	14	10	8	6	5	1	1	1
	P75	672	403.25	158.25	63	34		15	11	9	7	2	1	1
	P90	1181.20	684.10	255.10	92	49		20	15	12	10	3	1	1



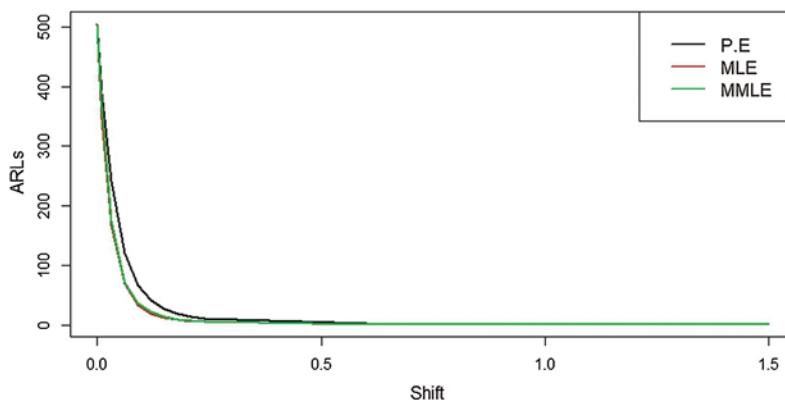
**Figure 5:** ARLs for the shape parameter of PFD under HEWMA control chart at  $\lambda_1 = 0.30$  and  $\lambda_2 = 0.60$

From [Tab. 6](#) and [Fig. 6](#), we observe that shift of 0.01 in the shape parameter of an underlying process, the control chart based on P.E detects the shift by giving  $ARL_1 = 388.178$ , the control chart based on MLE detects the shift  $ARL_1 = 344.91$ , and the control chart based on MMLE detects the shift at  $ARL_1 = 367.847$ . From [Tab. 7](#) and [Fig. 7](#), at shift = 0.01, the control chart based on P.E detects the shift and gives  $ARL_1 = 390.57$ , the control chart based on MLE gives  $ARL_1 = 358.786$ , and the control chart based on MMLE detects the shift at  $ARL_1 = 373.21$ .



**Table 6:** HEWMA control chart when  $\lambda_1 = 0.30$ ,  $\lambda_2 = 0.60$  based on P.E, MLE and MMLE for power function distribution

Estimation methods	Shift													
	0	0.01	0.03	0.06	0.09	0.120	0.150	0.180	0.210	0.240	0.60	1.00	1.5	
P.E L = 3.82	ARL	500.618	388.178	241.246	121.342	67.332	41.656	27.419	18.982	14.392	11.159	2.64	1.477	1.069
	SDRL	491.464	373.008	234.365	116.36	60.97	37.25	25.117	15.797	11.90	7.99	1.2435	0.593	0.253
	P10	58.00	45.90	27.00	16.00	11.0	8.0	6	5	4	4	1	1	1
	P25	152.5	113.75	71	36.75	22.0	15	11	8	7	6	2	1	1
	P50	365.5	291.50	161	89.00	50.0	30	19	14	11	9	2	1	1
	P75	694.75	528.50	337.25	161.00	94.0	56	36	26	18	14	3	2	1
MLE L = 3.98	ARL	500.865	344.915	167.066	69.494	33.419	18.855	12.175	8.664	6.614	5.328	1.616	1.057	1
	SDRL	524.0715	378.1097	161.993	65.779	27.91262	15.154	9.3760	5.61468	3.8735	2.860174	0.648	0.2319586	0
	P10	68.00	43.0	24.00	11.00	7	5.00	4	3	3	2	1	1	1
	P25	159.75	106.0	53.00	23.00	13	8.00	6	5	4	3	1	1	1
	P50	369.00	252.0	115.00	51.00	26	14.00	9	7	6	5	2	1	1
	P75	725.25	478.5	223.25	94.25	45	25.25	15	11	8	7	2	1	1
MMLE L = 4.09	ARL	500.494	367.847	176.29	70.75	35.692	21.44	14.027	9.711	7.326	5.754	1.569	1.051	1
	SDRL	479.607	348.9006	169.301	66.00	31.77	18.477	11.858	7.181	4.992	3.7012	0.716	0.22	0
	P10	63.8	43.00	25.0	9.9	6	5	4	3	2	2	1	1	1
	P25	156.5	96	56	23	13	8	6	5	4	3	1	1	1
	P50	382	245	121.5	50	27	16	11	8	6	5	1	1	1
	P75	670	486.25	240.5	98	48	29	19	13	9	7	2	1	1
P90	1120.2	771.30	395.1	160.1	78	44	28	19	13	10	3	1	1	



**Figure 6:** ARLs for the shape parameter of PFD under HEWMA control chart at  $\lambda_1 = 0.30$  and  $\lambda_2 = 0.10$

We also observe that HEWMA control chart performs better as compare to EWMA control chart and Shewhart control chart under all three estimation methods, i.e., P.E, MLE and MMLE by giving less  $ARL_1$  value, which means early detection of any shift in the process.

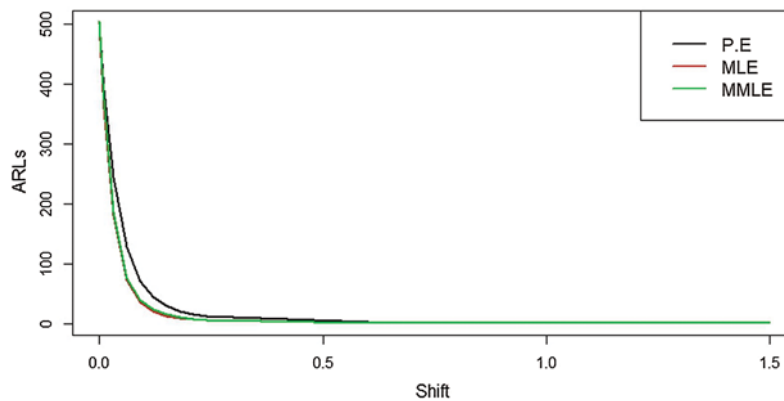
### 6.1 Simulated Data Set

To see the working procedure of the proposed control charts, a simulation study was carried out. For this purpose, we generated 25 observations from a PFD for an in-control process, and the next 25 observations were generated from the shifted process with  $\lambda = 0.10$ . The estimated

values of the proposed EWMA statistic under MLE were computed for the selected levels of the proposed control charts parameters with  $\lambda = 0.10$  and  $L = 4.20$ . The data and values of the proposed and existing statistic are listed in Tab. 8, and the plotted values of these statistics are shown in Fig. 8. Further, the estimated values of the proposed HEWMA statistic under MLE were computed for the selected levels of the proposed control charts parameters with  $\lambda_1 = 0.30$ ,  $\lambda_2 = 0.10$  and  $L = 4.065$ . The data and values of the proposed and existing statistic are listed in Tab. 8, and the plotted values of these statistics are shown in Fig. 9.

**Table 7:** HEWMA control chart when  $\lambda_1 = 0.30$ ,  $\lambda_2 = 0.75$  based on P.E, MLE and MMLE for power function distribution

Estimation methods		Shift												
		0	0.01	0.03	0.06	0.09	0.120	0.150	0.180	0.210	0.240	0.60	1.00	1.5
P.E L = 3.885	ARL	501.246	390.57	243.507	128.215	70.771	44.065	29.609	20.217	15.009	11.855	2.64	1.455	1.063
	SDRL	476.8266	365.166	239.856	123.4077	64.88	39.8348	26.728	16.93	12.624	8.9174	1.289	0.5901	0.243
	P10	56.90	50.0	27.00	16.00	11	9.0	6	5.0	4	3	1	1	1
	P25	150.0	115	72	39	23	16	11	9	7	6	2	1	1
	P50	368.0	290.5	162	91.50	53	31.5	21	15	12	10	2	1	1
	P75	695.75	544.0	334.25	172.25	96	58	40	27	19	15	3	2	1
	P90	1130.0	887.5	572.30	299.10	161	97.1	63	42.1	30	24	4	2	1
MLE L = 3.98	ARL		358.786	179.849	72.938	35.568	20.248	12.6	8.896	6.733	5.404	1.575	1.045	1
	SDRL	506.899	379.3842	178.4702	67.5058	30.464	16.5718	9.5755	6.0970	4.1406	3.0394	0.6471	0.2074	0
	P10	65.00	43.90	24.0	11.0	7	5	4	3	2	2	1	1	1
	P25	157.00	104.75	56.0	27.0	13	8	6	5	4	3	1	1	1
	P50	370.00	256.00	127.0	54.0	27	15	10	7	6	5	1	1	1
	P75	705.75	500.25	238.0	99.0	48	27	16	11	9	7	2	1	1
	P90	1173.30	857.20	416.1	156.1	77	41	25	17	12	10	2	1	1
MMLE L = 4.1535	ARL	504.232	373.21	186.184	76.063	38.633	23.069	14.863	10.367	7.576	6.018	1.596	1.054	1
	SDRL	475.515	331.5469	187.3311	70.932	34.517	20.40	12.722	7.7945	5.28	4.008	0.733	0.2261	0
	P10	60.90	47.00	26.00	10.0	7.0	5	4	3	2	2	1	1	1
	P25	147.75	104.75	57	24	13	9	6	5	4	3	1	1	1
	P50	379	266	122.50	54.5	29	17	11	8	6	5	1	1	1
	P75	707.25	507	254.25	105	53	31	19	14	10	8	2	1	1
	P90	1127	812.6	421.10	178	81.2	48	31	20	14	11	3	1	1

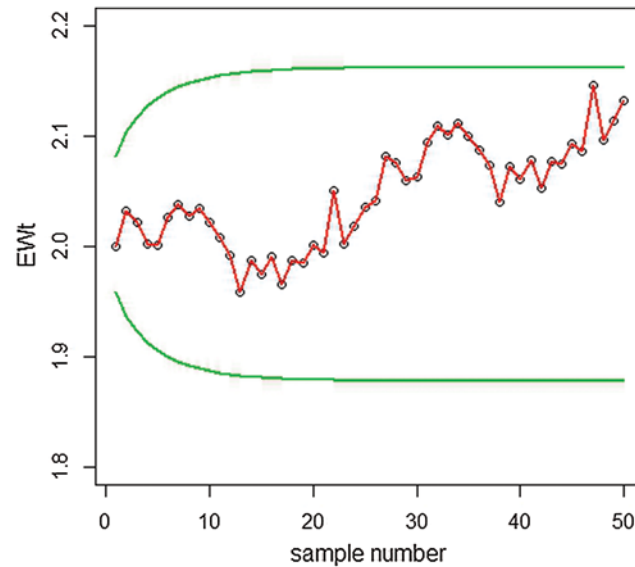


**Figure 7:** ARLs for the shape parameter of PFD under HEWMA control chart at  $\lambda_1 = 0.30$  and  $\lambda_2 = 0.75$

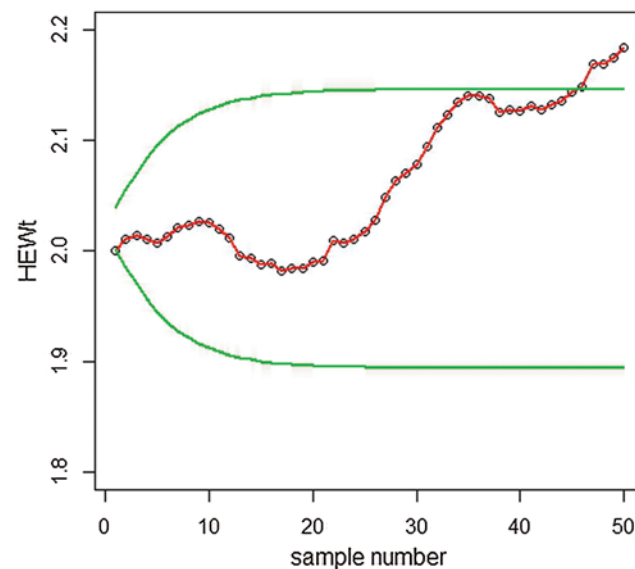
**Table 8: Simulated data**

EWMA			HEWMA			
$\lambda = 0.10$ and $L = 4.20$			$\lambda_1 = 0.30, \lambda_2 = 0.10$ and $L = 4.065$			
$EW_t$	LCL	UCL	$EW_t$	$HEW_t$	LCL	UCL
1.999742	1.958025	2.081975	1.999742	1.999922	2.001297	2.038704
2.032648	1.936621	2.103379	2.032648	2.009740	1.984710	2.055290
2.022034	1.922676	2.117324	2.022034	2.013428	1.969518	2.070482
2.0s01997	1.912700	2.127300	2.001997	2.009999	1.956267	2.083733
2.000829	1.905254	2.134746	2.000829	2.007248	1.945017	2.094983
2.026739	1.899560	2.140440	2.026739	2.013095	1.935621	2.104379
2.038168	1.895137	2.144863	2.038168	2.020617	1.927854	2.112146
2.027747	1.891667	2.148333	2.027747	2.022756	1.921479	2.118521
2.034679	1.888923	2.151077	2.034679	2.026333	1.916270	2.123730
2.021543	1.886742	2.153258	2.021543	2.024896	1.912028	2.127972
2.007367	1.885002	2.154998	2.007367	2.019637	1.908582	2.131418
1.991564	1.883608	2.156392	1.991564	2.011215	1.905786	2.134214
1.958908	1.882489	2.157511	1.958908	1.995523	1.903520	2.136480
1.987081	1.881590	2.158410	1.987081	1.992991	1.901684	2.138316
1.974873	1.880866	2.159134	1.974873	1.987555	1.900198	2.139802
1.990290	1.880282	2.159718	1.990290	1.988376	1.898995	2.141005
1.965196	1.879811	2.160189	1.965196	1.981422	1.898022	2.141978
1.987566	1.879430	2.160570	1.987566	1.983265	1.897234	2.142766
1.984756	1.879123	2.160877	1.984756	1.983712	1.896597	2.143403
2.001607	1.878874	2.161126	2.001607	1.989081	1.896081	2.143919
1.993854	1.878673	2.161327	1.993854	1.990513	1.895664	2.144336
2.050537	1.878511	2.161489	2.050537	2.008520	1.895326	2.144674
2.002203	1.878379	2.161621	2.002203	2.006625	1.895052	2.144948
2.018215	1.878273	2.161727	2.018215	2.010102	1.894831	2.145169
2.035307	1.878186	2.161814	2.035307	2.017664	1.894652	2.145348
2.041714	1.878117	2.161883	2.049882	2.027329	1.894507	2.145493
2.081554	1.878060	2.161940	2.097811	2.048474	1.894389	2.145611
2.075656	1.878014	2.161986	2.097980	2.063326	1.894294	2.145706
2.059292	1.877977	2.162023	2.086613	2.070312	1.894217	2.145783
2.062785	1.877947	2.162053	2.095690	2.077926	1.894155	2.145845
2.094064	1.877923	2.162077	2.132933	2.094428	1.894104	2.145896
2.109171	1.877903	2.162097	2.152481	2.111844	1.894063	2.145937
2.100904	1.877888	2.162112	2.147280	2.122475	1.894030	2.145970
2.111034	1.877875	2.162125	2.161188	2.134089	1.894003	2.145997
2.100044	1.877864	2.162136	2.153015	2.139766	1.893981	2.146019
2.087353	1.877856	2.162144	2.142497	2.140586	1.893964	2.146036
2.073221	1.877849	2.162151	2.130599	2.137590	1.893949	2.146051
2.040269	1.877843	2.162157	2.098207	2.125775	1.893938	2.146062
2.072167	1.877839	2.162161	2.133811	2.128186	1.893929	2.146071
2.060706	1.877835	2.162165	2.123595	2.126809	1.893921	2.146079
2.077973	1.877832	2.162168	2.142918	2.131641	1.893915	2.146085
2.052867	1.877830	2.162170	2.118326	2.127647	1.893910	2.146090
2.077280	1.877828	2.162172	2.144852	2.132809	1.893906	2.146094
2.075126	1.877826	2.162174	2.143642	2.136058	1.893903	2.146097
2.093397	1.877825	2.162175	2.163427	2.144269	1.893900	2.146100
2.085676	1.877824	2.162176	2.156065	2.147808	1.893898	2.146102
2.146482	1.877823	2.162177	2.220477	2.169608	1.893896	2.146104
2.096218	1.877822	2.162178	2.168953	2.169412	1.893895	2.146105
2.113459	1.877822	2.162178	2.187411	2.174811	1.893894	2.146106
2.131736	1.877821	2.162179	2.206847	2.184422	1.893893	2.146107

In Fig. 9, we noted that the proposed HEWMA control chart under MLE detected a shift at the 32th sample, while in Fig. 8; the EWMA control chart under MLE could not detect the shift. Hence, this shows that the proposed HEWMA control chart under MLE has a greater ability to detect smaller shifts earlier than the EWMA control chart.



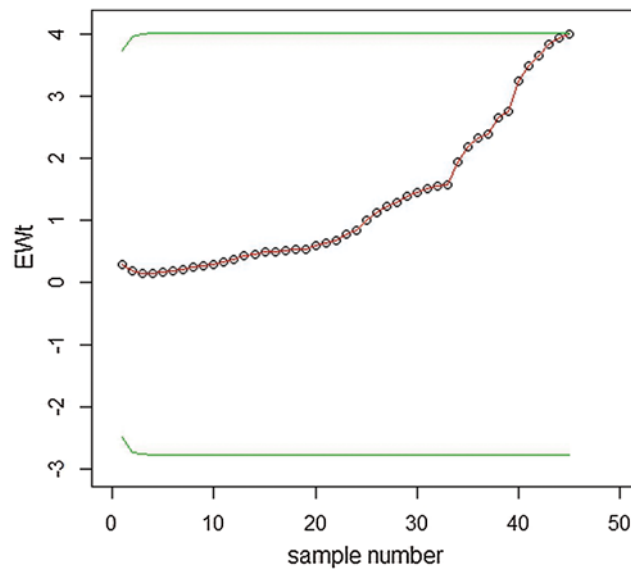
**Figure 8:** Graph of simulated data of the proposed EWMA control chart under MLE



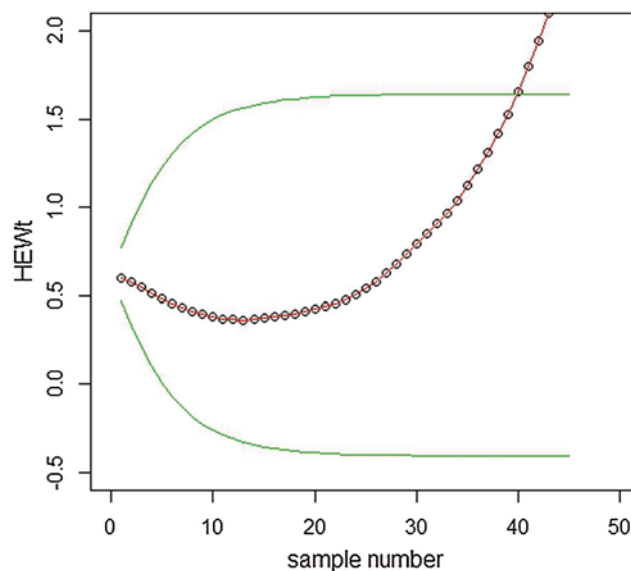
**Figure 9:** Graph of simulated data of the proposed HEWMA control chart under MLE

**6.2 Real Life Application**

The data set is reported by Bekker et al. [26], which corresponds to the survival times (in years) of a group of patients given chemotherapy treatment alone. The data consisting of survival times (in years) for 46 patients are: 0.047, 0.115, 0.121, 0.132, 0.164, 0.197, 0.203, 0.260, 0.282, 0.296, 0.334, 0.395, 0.458, 0.466, 0.501, 0.507, 0.529, 0.534, 0.540, 0.641, 0.644, 0.696, 0.841, 0.863, 1.099, 1.219, 1.271, 1.326, 1.447, 1.485, 1.553, 1.581, 1.589, 2.178, 2.343, 2.416, 2.444, 2.825, 2.830, 3.578, 3.658, 3.743, 3.978, 4.003, 4.033. The data follows the PFD and plotted for both EWMA and HEWMA control charts under MLE, as shown in Figs. 10 and 11.



**Figure 10:** Graph of real data of the EWMA control chart under MLE when  $L = 4.20$  and  $\lambda = 0.10$



**Figure 11:** Graph of real data of the HEWMA control chart under MLE when  $\lambda_1 = 0.30$ ,  $\lambda_2 = 0.10$  and  $L = 4.30$

We have constructed EWMA for  $\lambda = 0.10$  and HEWMA for  $\lambda_1 = 0.30$ ,  $\lambda_2 = 0.10$  control charts under MLE in Figs. 10 and 11. We see that HEWMA detects the process shift early compared to EWMA, which shows that HEWMA is better to be used in real life when the distribution of the underlying process is PFD.

## 7 Conclusion

If the process characteristic follows power function distribution, the construction of the usual control charts such as Shewhart control chart, EWMA control chart and HEWMA control chart by assuming the assumption of normality may increase the chances of the use of inappropriate chart which leads to the wrong detection of real changes in the process, to overcome such issue, we have constructed the Shewhart, EWMA and HEWMA control charts by assuming that the distribution of the process is power function distribution. We have used three different estimation methods for the shape parameter of PFD to construct the said control charts. We have concluded that the HEWMA control chart under MLE performs better as compared to the other control charts.

We have used the EWMA and HEWMA control chart under MLE to simulate data and constructed the control charts; We observe that HEWMA under MLE is better to be used for monitoring the process shape parameter. We have also provided the real-life application of the proposed control charts. We observe that when the distribution of process follows PFD, HEWMA control chart under MLE is preferred to be used.

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**Conflicts of Interest:** The authors declare that they have no conflicts of interest to report regarding the present study.

## References

1. Roberts, S. W. (1959). Control chart tests based on geometric moving averages. *Technometrics*, 1(3), 239–250. DOI 10.1080/00401706.1959.10489860.
2. Li, Z., Xie, M., Zhou, M. (2018). Rank-based EWMA Procedure for sequentially detecting changes of process location and variability. *Quality Technology & Quantitative Management*, 15(3), 354–373. DOI 10.1080/16843703.2016.1208941.
3. Nguyen, H. D., Tran, K. P., Heuchenne, C. (2019). Monitoring the ratio of two normal variables using variable sampling interval exponentially weighted moving average control charts. *Quality and Reliability Engineering*, 35(1), 439–460. DOI 10.1002/qre.2412.
4. Page, E. S. (1954). Continuous inspection scheme. *Biometrika*, 41(2), 100–115. DOI 10.1093/biomet/41.1-2.100.
5. Sanusi, R. A., Riaz, M., Abbas, N. (2017). Combined Shewhart CUSUM charts using auxiliary variable. *Computers & Industrial Engineering*, 105(6), 329–337. DOI 10.1016/j.cie.2017.01.018.
6. Haq, A., Munir, W. (2018). Improved CUSUM charts for monitoring process mean. *Journal of Statistical Computation and Simulation*, 88(9), 1684–1701. DOI 10.1080/00949655.2018.1444040.
7. Hossain, M. P., Sanusi, R. A., Omar, M. H., Riaz, M. (2019). On designing Maxwell CUSUM control chart: An efficient way to monitor failure rates in boring processes. *International Journal of Advanced Manufacturing Technology*, 100(5–8), 1923–1930. DOI 10.1007/s00170-018-2679-1.
8. Abbas, N., Riaz, M., Does, R. J. M. M. (2013). Mixed exponentially weighted moving average-cumulative sum charts for process monitoring. *Quality and Reliability Engineering International*, 29(3), 345–356. DOI 10.1002/qre.1385.

9. Ajadi, J. O., Riaz, M. (2017). Mixed multivariate EWMA-CUSUM control charts for an improved process monitoring. *Communications in Statistics-Theory and Methods*, 46(14), 6980–6993. DOI 10.1080/03610926.2016.1139132.
10. Shamma, S. E., Shamma, A. K. (1992). Development and evaluation of control charts using double exponentially weighted moving averages. *International Journal of Quality and Reliability Management*, 9(6), 18–25. DOI 10.1108/02656719210018570.
11. Haq, A. (2013). A new hybrid exponentially weighted moving average control chart for monitoring process mean. *Quality and Reliability Engineering International*, 29(7), 1015–1025. DOI 10.1002/qre.1453.
12. Noorossana, R., Fathizadan, S., Nayebpour, M. R. (2016). EWMA control chart performance with estimated parameters under non-normality. *Quality and Reliability Engineering International*, 32(5), 1637–1654. DOI 10.1002/qre.1896.
13. Lin, Y. C., Chou, C. Y., Chen, C. H. (2017). Robustness of the EWMA median control chart to non-normality. *International Journal of Industrial and Systems Engineering*, 25(1), 35–58. DOI 10.1504/IJISE.2017.080687.
14. Hossain, P., Omar, M. H., Riaz, M. (2017). New V control chart for the Maxwell distribution. *Journal of Statistical Computation and Simulation*, 87(3), 594–606. DOI 10.1080/00949655.2016.1222391.
15. Erto, P., Pallotta, G., Palumbo, B., Mastrangelo, C. M. (2018). The performance of semi empirical Bayesian control charts for monitoring Weibull data. *Quality Technology & Quantitative Management*, 15(1), 69–86. DOI 10.1080/16843703.2017.1304036.
16. Ahmed, A., Sanaullah, A., Hanif, M. (2019). A robust alternate to the HEWMA control chart under non-normality. *Quality Technology & Quantitative Management*, 17(4), 423–447. DOI 10.1080/16843703.2019.1662218.
17. Liang, W., Xiang, D., Pu, X., Li, Y., Jin, L. (2019). A robust multivariate sign control chart for detecting shifts in covariance matrix under the elliptical directions distributions. *Quality Technology & Quantitative Management*, 16(1), 113–127. DOI 10.1080/16843703.2017.1372852.
18. Khan, Z., Gulistan, M., Kadry, S., Chu, Y., Lane-Krebs, K. (2020). On scale parameter monitoring of the rayleigh distributed data using a new design. *IEEE Access*, 8, 188390–188400. DOI 10.1109/ACCESS.2020.3030710.
19. Dallas, C. (1976). Characterization of Pareto and POWER function distribution. *Annals of the Institute of Statistical Mathematics*, 28(1), 491–497. DOI 10.1007/BF02504764.
20. Meniconi, M., Barry, D. M. (1996). The Power function distribution: A useful and simple distribution to assess electrical component reliability. *Microelectron Reliab*, 36(9), 1207–1212. DOI 10.1016/0026-2714(95)00053-4.
21. Shewhart, W. A. (1931). *Economic Control of manufactured product*. London: Macmillan.
22. Zaka, A., Akhter, A. S. (2013). Methods for estimating the parameters of the Power function distribution. *Pakistan Journal of Statistics and Operational Research*, 9(2), 213–224. DOI 10.18187/pjsor.v9i2.488.
23. Zaka, A., Akhter, A. S. (2014). Modified moment, maximum likelihood and percentile estimators for the parameters of the power function distribution. *Pakistan Journal of Statistics and Operational Research*, 10(4), 361–368. DOI 10.18187/pjsor.v10i3.825.
24. Dubey, S. D. (1967). Some percentile estimators for Weibull parameters. *Technometrics*, 9(1), 119–129. DOI 10.1080/00401706.1967.10490445.
25. Marks, N. B. (2005). Estimation of Weibull parameters from common percentiles. *Journal of Applied Statistics*, 32(1), 17–24. DOI 10.1080/0266476042000305122.
26. Bekker, A., Roux, J., Mostert, P. (2000). A generalization of the compound Rayleigh distribution: Using Bayesian methods on cancer survival times. *Communication in Statistics Theory and Methods*, 29(7), 1419–1433. DOI 10.1080/03610920008832554.