# **Analytical Explicit Formulas of Average Run Length of DEWMA Control Chart based on Seasonal Moving Average Process**

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*Abstract: -* The primary objective of this research is to propose explicit formulas for the Average Run Length (ARL) of the Double Exponentially Weighted Moving Average control chart (DEWMA) for the Seasonal Moving Average process (SMA  $(Q)_L$ ) with exponential white noise. The Numerical Integral Equation by the midpoint rule is employed to compare the results derived from the formulas and evaluate their accuracy using the percentage of accuracy (%Acc). The DEWMA control chart's efficacy is measured by calculating the average run length (ARL), median run length (MRL), and standard deviation of run length (SDRL). Significant agreement was observed between the numerical approximations and the explicit formulations for  $SMA(2)<sub>4</sub>$  and  $SMA(3)<sub>12</sub>$  processes. This finding indicates the formulations are sufficiently precise. A comparison of Exponentially Weighted Moving Average (EWMA) and DEWMA control charts relating to mean process variations is performed. For practical data, WTI oil prices are used to determine the efficacy of the explicit formula approach.

*Key-Words: -* Average Run Length, Seasonal Moving Average Process, Double Exponentially Weighted Moving Average, Exponential white noise, Numerical Integral Equation, Midpoint rule.

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## **1 Introduction**

A statistical process control method is a quality control approach that employs statistical methods to control and monitor a process. It is extensively employed in numerous areas such as telecommunications, education, energy production, healthcare, finance, and software development to guarantee that processes remain consistent, predictable, and within specified limits, [1], [2], [3]. The Shewhart control chart effectively identifies significant changes in the process's mean, as described by [4]. However, the Cumulative Sum (CUSUM) and the exponential weighted Moving Average (EWMA) control schemes are more effective in identifying minor to moderate changes. The study, [5], presented the CUSUM control chart, which is particularly suitable for monitoring processes for small changes. The CUSUM chart exhibits more sensitivity to small changes than the

Shewhart control chart, which makes it a valuable tool for proactive quality management. Subsequently, the EWMA control chart was introduced into the study, [6]. In statistical process control, an EWMA control chart is utilized to monitor and identify shifts in the process mean. This control chart gives more weight to recent observations, making them more responsive to changes than the traditional Shewhart control chart. The advantages of utilizing the EWMA control chart are supported by the study, [7], [8]. Recently, an alternative to the traditional EWMA control chart was developed and called the Double Exponentially Weighted Moving Average (DEWMA) control chart, [9]. The DEWMA control chart benefits processes that exhibit both short-term and long-term shifts. The main idea is to obtain two levels of smoothing parameters. The DEWMA control chart is suitable for detecting small changes in the mean of a process with normally distributed observations. It is more effective than the EWMA control chart in detecting minor shifts, [10], [11].

Autocorrelation in time series data refers to the correlation of a series with its past and future values. The Box-Jenkins methodology, specifically the Autoregressive Integrated Moving Average (ARIMA) model, is commonly used to handle autocorrelated data. A Seasonal Moving Average process  $(SMA(Q)_L)$  is a time series analysis technique that combines moving averages with a seasonal component. It is designed to capture both the trend and the seasonal patterns in a time series data set. The seasonal moving average process is beneficial when dealing with data that exhibits regular and repeating patterns at specific intervals. The proper control charts must be applied to these data. Furthermore, residuals probably consist of some type of white noise. However, alternative displays, such as exponential white noise, could occur in particular datasets, [12], [13].

The average run length (ARL) is the primary metric to assess control chart approaches. It is computed for both in-control (ARL0) and out-ofcontrol (ARL1) scenarios. Before a process exceeds the control limit, its average run length is denoted as ARL0. In general, the ARL0 value should be sufficiently substantial. The mean of the observations collected from the beginning of the change process until it exceeds the control threshold is denoted by ARL1. Consequently, it is essential to minimize the ARL1 value.

ARL can be generally assessed using various techniques, including Monte Carlo simulation, the Markov Chain Approach (MCA), numerical integral equations (NIE), and explicit formulations. For example, the study [14] utilized Monte Carlo simulation to examine ARL for nonparametric double EWMA control charts based on the mood statistic for process variability. The study [15] investigated the ARL of EWMA and CUSUM control charts using the Markov Chain approach when the observation follows a zero-inflated negative binomial distribution. The numerical integral equation (NIE) method was employed to evaluate the effectiveness of the CUSUM control chart in approximating the ARL for a long-memory fractionally integrated autoregressive model with an exogenous variable in the study [16]. In addition, the ARL was determined through the research study [17] which employed the NIE technique for including Simpson's rules, Gaussian, midpoint, and trapezoidal rules into the extended exponentially weighted moving average control

chart. This approach was utilized when the observations followed continuous distributions, specifically the exponential, Weibull, and Gamma distributions. In addition, for the explicit formula method, which is a method that gives accurate value and high precision, the study [18] employed the integral equation approach to prove the ARL of the EWMA procedure for autocorrelated data.

From the research that has been done, no researcher has investigated the exact formula for the Average Run Length (ARL) of the DEWMA control chart for  $SMA(Q)<sub>L</sub>$  models. Consequently, developing an explicit formula for the ARL on the DEWMA control chart for the  $SMA(Q)<sub>L</sub>$  model is the objective of this research. Likewise, an evaluation of the effectiveness of the EWMA control chart is included. Furthermore, to evaluate the effectiveness of the DEWMA control chart, the WTI crude oil price dataset was utilized. Based on the information provided, studies have yet to be carried out with the exact formula for the Average Run Length (ARL) of the DEWMA control chart.

## **2 Process and Control Charts**

### **2.1 Process**

Given  $Y_t$  be a sequence of Seasonal Moving Average random processes. The  $SMA(O)<sub>L</sub>$  process is the process of the random errors that occurred in past periods,  $\zeta_{t-L}, \zeta_{t-2L}, ..., \zeta_{t-QL}$ .

The general Seasonal Moving Average processes, denoted by the SMA  $(Q)$ <sub>L</sub> process, can be written as in Eq. (1):<br>  $Y_t = \theta_0 + \zeta_t - \theta_1 \zeta_{t-1} - \theta_2 \zeta_{t-2L} - \dots - \theta_0 \zeta_{t-QL}$ 

$$
C_{t} = \theta_{0} + \zeta_{t} - \theta_{1} \zeta_{t-L} - \theta_{2} \zeta_{t-2L} - \dots - \theta_{Q} \zeta_{t-QL}
$$
 (1)

where  $\zeta_i$  is an exponential white noise process. A seasonal moving average coefficient,  $-1 \le \theta_i \le 1$ .

The primary focus of this research is the one-sided control chart, which is used to examine the case of a positive change. The sequence of independent identical distribution random variables with exponential parameters is denoted as  $(\beta)$ . It is normally assumed that the known parameter for incontrol process given  $\beta = \beta_0$ . The parameter  $\beta$ could be changed to the out-of-control value  $\beta = \beta_1$ where  $\theta < \infty$ , and  $\theta$  is the change-point time.

### **2.2 The Double Exponentially Weighted Moving Average Control Chart**

The DEWMA control chart was initially introduced by [9]. Later, the study [11] improved the control chart's robustness by adjusting smoothing parameters. The DEWMA statistic is presented below in Eq.  $(2)$ .

$$
DE_t = \lambda_2 E_t + (1 - \lambda_2)DE_{t-1}
$$
 (2)

where  $E_t = \lambda_1 Y_t + (1 - \lambda_1) E_{t-1}$  is EWMA statistic,  $Y_t$ 

is a sequence of SMA(Q)<sub>L</sub> model,  $\lambda_1$  and  $\lambda_2$  are an exponential smoothing parameters,  $0 < \lambda_1, \lambda_2 \le 1$ . The upper control limit (UCL) and lower control limit (LCL) of the DEWMA control iven by<br> $\frac{\lambda_1^2 \lambda_2^2}{\sqrt{(\lambda_1^2 \lambda_2^2 + (\lambda_2^2)^2 + (\lambda_3^2 \lambda_3^2 + \lambda_4^2)^2)}} + \frac{(1-\lambda_1)^2}{2} - 2\frac{(1-\lambda_1)(1-\lambda_2)}{(1-\lambda_2)^2}$ y<br>  $\left[ \frac{(1-\lambda_2)^2}{2} + \frac{(1-\lambda_1)^2}{2} - 2 \frac{(1-\lambda_1)(1-\lambda_2)}{(1-\lambda_1)(1-\lambda_2)} \right]$ 



where  $\mu$  is the target mean,  $\sigma$  is the process standard deviation, and  $F_{DE}$  is width of the control limits. The stopping time of the DEWMA control chart  $(\tau_b)$  is given by

$$
\tau_b = \{t > 0; \, DE_t \ge b\},\,
$$

where  $\tau$ <sub>i</sub> is the stopping time and b is a UCL.

### **2.3 The Exponentially Weighted Moving Average Control Chart**

The design scheme for the EWMA control chart was initially proposed by [6]. It is frequently utilized to monitor processes and detect change. The following mathematical expression defines the EWMA control chart's statistical characteristics:  $E_t = \lambda Y_t + (1 - \lambda) E_{t-1}$ (3)

where  $Y_t$  is a sequence of SMA(Q)<sub>L</sub> model with exponential white noise, and  $\lambda$  is an exponential smoothing parameter  $(0 < \lambda \le 1)$ .

The UCL and LCL of the EWMA control chart are given by

$$
\mu \pm F_E \sigma \sqrt{\frac{\lambda}{2-\lambda}},
$$

where  $\mu$  is the target mean,  $\sigma$  is the process standard deviation, and  $F<sub>E</sub>$  is width of the control limits. The stopping time of the EWMA control chart  $(\tau_h)$  is represented as:

 $\tau_h = \{ t \geq 0 : E_t > h \}$ 

where  $\tau$ <sub>k</sub> is the stopping time, and *h* is a *UCL*.

### **3 The Method for Evaluation ARL**

#### **3.1 The Explicit Formula of ARL on DWMA Control Chart**

This section demonstrates proving the explicit formula of average run length (ARL) on the DEWMA control charts using the SMA (Q)<sup>L</sup> model. The proof begins by substituting Eq. (3) into Eq. (2) as follows:<br>  $DE_t = \lambda_1 \lambda_2 (\theta_0 + \zeta_1 - \theta_1 \zeta_{t-L} - \theta_2 \zeta_{t-2L} - ... - \theta_Q \zeta_{t-QL}) + \lambda_2 (1 - \lambda_1) E_{t-1}$ 

into Eq. (2) as follows:  
\n
$$
DE_{t} = \lambda_{1} \lambda_{2} \left( \theta_{0} + \zeta_{t} - \theta_{1} \zeta_{t-L} - \theta_{2} \zeta_{t-2L} - \dots - \theta_{Q} \zeta_{t-QL} \right) + \lambda_{2} (1 - \lambda_{1}) E_{t-1} + (1 - \lambda_{2}) DE_{t-1}
$$

when the first time  $t = 1$  such that  $DE_0 = \psi$  is determined, then the initial values  $E_0 = \gamma$  and  $\zeta_{t-L}, \zeta_{t-2L}, ..., \zeta_{t-QL}$  equal to 1. The DEWMA statistics with  $SMA(Q)<sub>L</sub>$  can be defined as follows: tistics with SMA(Q)<sub>L</sub> can be defined as follows:<br>  $\Gamma_1 = \lambda_1 \lambda_2 \left( \theta_0 + \zeta_1 - \theta_1 \zeta_{1-L} - \theta_2 \zeta_{1-2L} - \dots - \theta_Q \zeta_{1-QL} \right) + \lambda_2 (1 - \lambda_1) \gamma$  $+(1-\lambda_2)w$  $DE_1 = \lambda_1 \lambda_2 (\theta_0 + \zeta_1 - \theta_1 \lambda_2 + (1 - \lambda_2) \psi$ statistics with SMA(Q)<sub>L</sub> can be defined as follows:<br> $DE_1 = \lambda_1 \lambda_2 \left( \theta_0 + \zeta_1 - \theta_1 \zeta_{1-L} - \theta_2 \zeta_{1-2L} - \dots - \theta_Q \zeta_{1-QL} \right) + \lambda_2 (1 - \lambda_1) \gamma$  $(\theta_0 + \zeta_t - \theta_1 \zeta_t)$ stics with SMA(Q)<sub>L</sub> can be defined as follows:<br>=  $\lambda_1 \lambda_2 (\theta_0 + \zeta_1 - \theta_1 \zeta_{t-L} - \theta_2 \zeta_{t-2L} - ... - \theta_0 \zeta_{t-QL}) + \lambda_2 (1 - \lambda_1) \gamma$  $\lambda_1 \lambda_2 \left( \theta_0 + \zeta_t \right) + (1 - \lambda_2) \psi$ 

For in control process, the interval of  $DE_1$  that is in between the lower and upper control limits or from 0 to *b* can be written as follows.<br>  $0 < \lambda_1 \lambda_2 (\theta_0 - \theta_1 \zeta_{1-L} - \theta_2 \zeta_{1-2L} - ... - \theta_Q \zeta_{1-QL}) + \lambda_2 (1 - \lambda_1) \gamma$ 

$$
0 < \lambda_1 \lambda_2 (\theta_0 - \theta_1 \zeta_{1-L} - \theta_2 \zeta_{1-2L} - \dots - \theta_Q \zeta_{1-QL}) + \lambda_2 (1 - \lambda_1) \gamma + (1 - \lambda_2) \psi + \lambda_1 \lambda_2 \zeta_1 < b.
$$

Thus, the interval of 
$$
\zeta_1
$$
 can be expressed as:  
\n
$$
\left[\frac{-(1-\lambda_2)\psi}{\lambda_1\lambda_2} - \frac{\lambda_2(1-\lambda_1)\gamma}{\lambda_1\lambda_2} \right] < \zeta_1 < \left[\frac{b - (1-\lambda_2)\psi}{\lambda_1\lambda_2} - \frac{\lambda_2(1-\lambda_1)\gamma}{\lambda_1\lambda_2} - \frac{\lambda_2(1-\lambda_1)\gamma}{\lambda_1\lambda_2} \right]
$$
\n
$$
= \frac{\lambda_1\lambda_2(\theta_0 - \theta_1\zeta_{1-1} - \ldots - \theta_0\zeta_{1-QL})}{\lambda_1\lambda_2} \left[\frac{\lambda_1\lambda_2(\theta_0 - \theta_1\zeta_{1-1} - \ldots - \theta_0\zeta_{1-QL})}{\lambda_1\lambda_2}\right].
$$

Using the Fredholm integral equation, the ARL integral equation for the SMA(Q)L model with an initial value of  $DE_0 = \psi$  is determined on the DEWMA control chart. The expression for the equation appears as follows:

$$
H(\psi) = \begin{bmatrix} \frac{b - (1 - \lambda_2)\psi}{\lambda_1 \lambda_2} & \frac{\lambda_2 (1 - \lambda_1)\gamma}{\lambda_1 \lambda_2} & \frac{\lambda_1 \lambda_2 (6_0 - \theta_1 \zeta_{1-L} - \cdots - \theta_0 \zeta_{1-Qk})}{\lambda_1 \lambda_2} \\ \frac{1}{\lambda_1 \lambda_2} & \frac{1}{\lambda_2 \lambda_2} & \frac{1}{\lambda_1 \lambda_2} & \frac{\lambda_2 (6_0 - 6\zeta_{1-L} - \cdots - 6_0 \zeta_{1-Qk})}{\lambda_1 \lambda_2} \\ \frac{-(1 - \lambda_2)\psi}{\lambda_1 \lambda_2} & \frac{\lambda_2 (1 - \lambda_1)\gamma}{\lambda_1 \lambda_2} & \frac{\lambda_2 \lambda_2 (6_0 - 6\zeta_{1-L} - \cdots - 6_0 \zeta_{1-Qk})}{\lambda_1 \lambda_2} \end{bmatrix} H \begin{pmatrix} \lambda_1 \lambda_2 \theta_0 - \theta_1 \zeta_{1-L} - \cdots - \theta_p \zeta_{1-Pk} \\ + \lambda_2 (1 - \lambda_1)\gamma + (1 - \lambda_2)\psi + \lambda_1 \lambda_2 \zeta_1 \end{pmatrix}
$$

Given

Given  
\n
$$
v = \lambda_1 \lambda_2 \left( \theta_0 - \theta_1 \zeta_{1-L} - \theta_2 \zeta_{1-2L} - \dots - \theta_Q \zeta_{1-QL} \right) + \lambda_2 (1 - \lambda_1) \gamma + (1 - \lambda_2) \psi + \lambda_1 \lambda_2 \zeta_1
$$

Then, 
$$
H(\psi)
$$
 can be rewritten as follows:  
\n
$$
H(\psi) = 1 + \frac{1}{\lambda_1 \lambda_2} \times
$$
\n
$$
\int_0^b H(\upsilon) f\left(\frac{\eta - (1 - \lambda_2)\psi - \lambda_1 \lambda_2 (\theta_0 - \theta_1 \zeta_{1-L} - \dots - \theta_0 \zeta_{1-\rho L}) - \lambda_2 (1 - \lambda_1) \gamma}{\lambda_1 \lambda_2}\right) d\upsilon
$$
\n(4)

From Eq. (4), the function of  $\zeta_1$  has an exponential distribution. Consequently,  $H(\psi)$  can be represented as follows:

$$
H(\psi) = 1 + \frac{e^{\frac{(1-\lambda_2)\psi}{\beta \lambda_1 \lambda_2} \cdot \frac{\lambda_2 (1-\lambda_1)\gamma}{\beta \lambda_1 \lambda_2} \cdot e^{\frac{\lambda_1 \lambda_2 (\theta_0 - \theta_1 \zeta_{1-L} - \dots - \theta_0 \zeta_{1-\theta L})}{\beta}}}}{\beta \lambda_1 \lambda_2}
$$
(5)  

$$
\times \int_0^b H(\upsilon) \cdot e^{\frac{-\upsilon}{\beta \lambda_1 \lambda_2}} d\upsilon.
$$

The ARL solution is verified by Banach's fixed-point theorem. This holds for the ARL solution that the solution exists and has uniqueness. From Eq. (5), we suppose that

$$
h(\psi) = \frac{e^{\frac{(1-\lambda_2)\psi}{\beta \lambda_1 \lambda_2}} \cdot e^{\frac{\lambda_2(1-\lambda_1)\gamma}{\beta \lambda_1 \lambda_2}} \cdot e^{\frac{\lambda_1 \lambda_2 (\theta_0 - \theta_1 \zeta_{1-L} - \dots - \theta_0 \zeta_{1-\theta L})}{\beta}}}{\beta \lambda_1 \lambda_2}
$$
  
and  $\phi = \int_0^b H(v) \cdot e^{\frac{-v}{\beta \lambda_1 \lambda_2}} dv$ .

Therefore, the ARL solution contained in Eq. (5) can be rewritten by reformatting the variables as follows:

$$
H(\psi) = 1 + h(\psi) \cdot o \tag{6}
$$

The integral equation of  $o$ , which can be expressed as follows:

expressed as follows:  
\n
$$
o = \int_{0}^{b} \frac{-v}{e^{\beta \lambda_1 \lambda_2}} \left[ 1 + \frac{e^{\frac{(1-\lambda_2)y}{\beta \lambda_1 \lambda_2}} \cdot e^{\frac{\lambda_2 (1-\lambda_1)y}{\beta \lambda_1 \lambda_2}} \cdot e^{\frac{\lambda_1 \lambda_2 ( \theta_0 - \theta_1 \zeta_{1-L} - \cdots - \theta_0 \zeta_{1-\theta L})}{\beta}}}{\beta \lambda_1 \lambda_2} \cdot o \right] dv
$$
\n
$$
o = \frac{-\beta \lambda_1 \lambda_2 \left[ e^{\frac{-b}{\beta \lambda_1 \lambda_2}} - 1 \right]}{\beta \lambda_1 \lambda_2} \cdot \left[ e^{\frac{-b}{\beta \lambda_1 \lambda_2}} - 1 \right]} \cdot (7)
$$
\n
$$
1 + \frac{e^{\frac{\lambda_1 \lambda_2 (\theta_0 - \theta_1 \zeta_{1-L} - \theta_2 \zeta_{1-2L} - \cdots - \theta_0 \zeta_{1-\theta L}) + \lambda_2 (1-\lambda_1)y}{\beta \lambda_1 \lambda_2}}}{\lambda_2} \cdot \left[ e^{\frac{-b}{\beta \lambda_1}} - 1 \right]
$$

Subsequently, the solution of  $\sigma$  is substituted into Eq.(6), as illustrated in Eq.(7), which is obtained as:

obtained as:  
\n
$$
\lambda_{2}e^{\frac{(1-\lambda_{2})\psi}{\beta\lambda_{1}\lambda_{2}}}\cdot\left[e^{\frac{-b}{\beta\lambda_{1}\lambda_{2}}}-1\right]
$$
\n
$$
\lambda_{2}e^{\frac{\lambda_{1}\lambda_{2}(\theta_{0}-\theta_{1}\zeta_{1-L}-\cdots-\theta_{0}\zeta_{1-\theta_{L}})+\lambda_{2}(1-\lambda_{1})\gamma}{\beta\lambda_{1}\lambda_{2}}}+\left[e^{\frac{-b}{\beta\lambda_{1}}}-1\right]
$$
\n(8)

The explicit Average Run Length (ARL) formula for the  $SMA(Q)<sub>L</sub>$  model is provided in Eq. (8), which is used for the DEWMA control chart.

Furthermore, the process that is in control is substituted  $\beta$  with  $\beta_0$ , whereas the process that is out of control is substituted  $\beta$  with  $\beta_1$ .

#### **3.2 The Numerical Integral Equation of ARL on DEWMA control chart**

The average run length results are compared using the explicit formula method with the numerical integral equation or NIE method. Let  $J(\psi)$  refer to the ARL of the DEWMA control chart for the  $SMA(Q)<sub>L</sub>$  model. The approximation of the ARL is performed using the midpoint rule. The interval  $[0, b]$  is divided into  $0 \leq v_1 \leq$  $v_2 \leq ... \leq v_m \leq b$  using a set of constant weights  $w_{j} = b / m$ .

The evaluation of the integral approximation is conducted as follows:

$$
\int_{0}^{b} H(v)f(v)dv \approx \sum_{j=1}^{m} w_{j}f(v_{j})
$$
\n(9)

Denote the integral equation using a numerical approximation in the form of  $J(v_i)$ . It is obtained

through the solution of the linear equations:  
\n
$$
J(v_i) = 1 + \frac{1}{\lambda_i \lambda_2} \sum_{j=1}^{m} J(v_j)
$$
\n
$$
\times f\left(\frac{v_j - (1 - \lambda_2)\psi - \lambda_1 \lambda_2 (\theta_0 - \theta_1 \zeta_{1-L} - \dots - \theta_0 \zeta_{1-QL}) - \lambda_2 (1 - \lambda_1) \gamma}{\lambda_1 \lambda_2}\right)
$$
\n
$$
i = 1, 2, ..., m.
$$
\n(10)

The *m* linear equation system is expressed as  $H_{m \times 1} + R_{m \times m} H_{m \times 1}$ . If the inverse  $(I_m - R_{m \times m})^{-1}$  exists, the unique solution is presented as:

$$
H_{m\times 1} = (I_m - R_{m\times m})^{-1} \cdot 1_{m\times 1},
$$

where  $H_{m\times 1} = [J(v_1), J(v_2), ..., J(v_m)]',$ diag(1,1,...,1) is the unit matrix order *m*,  $1_{m\times 1} = [1,1,...,1]'$  is a column vector of  $J(v_i)$ , and  $R_{m \times m}$  is a matrix, the  $(m,m<sup>th</sup>)$  elements of *R* matrix

are defined as  
\n
$$
[R_{ij}] \approx \frac{1}{\lambda_1 \lambda_2} w_j
$$
\n
$$
\times f\left(\frac{\nu_j - (1 - \lambda_2)\psi - \lambda_1 \lambda_2 \left(\theta_0 - \theta_1 \zeta_{1-L} - \dots - \theta_0 \zeta_{1-QL}\right) - \lambda_2 (1 - \lambda_1) \gamma}{\lambda_1 \lambda_2}\right)
$$

Finally,  $v_i$  is instead of  $\psi$  into  $J(v_i)$ , The ARL estimation using the NIE method is shown as follows:

$$
J(\psi) \approx 1 + \frac{1}{\lambda_1 \lambda_2} \sum_{j=1}^{m} J(\psi_j)
$$
  
\$\times f\left(\frac{\nu\_j - (1 - \lambda\_2)\psi - \lambda\_1 \lambda\_2 \left(\theta\_0 - \theta\_1 \zeta\_{1-L} - \dots - \theta\_0 \zeta\_{1-QL}\right) - \lambda\_2 (1 - \lambda\_1)\gamma}{\lambda\_1 \lambda\_2}\right)\$ (11)

where  $U_j$  represents a set of interval division points  $v_j = (j-0.5)w_j$  for  $j = 1, 2, ..., m$  and  $w_j$  is a weight of the composite midpoint formula;  $w_j = b / m$ .

#### **3.3 The Uniqueness and Existence of the Explicit ARL Formula**

In this section, the Banach fixed-point theorem is used to prove that the explicit formula of the ARL has an existence and gives a unique solution.

**Theorem 1 Banach's Fixed-point Theorem:** Let  $(Y, d)$  be a complete metric space and let  $T: Y \rightarrow Y$ be a contraction mapping on *Y*. Then, *T* has a unique fixed point  $y \in Y$  (such that  $T(y) = y$ ) with contraction constant  $s \in [0,1)$  such that

with contraction constant  $s \in [0,1)$  such that<br>  $T(H(\psi)_1) - T(H(\psi)_2) \leq s \|H(\psi)_1 - H(\psi)_2\|$ , for all  $H(\psi)_1, H(\psi)_2 \in Y$ . There exists a unique  $H(\psi) \in Y$ such that  $T(H(\psi)) = H(\psi)$ , i.e., a unique fixedpoint in *Y* .

**Proof:** Specify T in Eq. (9) is a contraction mapping for  $H(\psi)$ ,  $H(\psi)$ <sub>2</sub>  $\in$   $u[0,b]$ .

To illustrate that

 $T(H(\psi)_1) - T(H(\psi)_2) \| \le s \| H(\psi)_1 - (H(\psi)_2) \|$  for all

 $H(\psi)_{1}, H(\psi)_{2} \in Y$  with  $s \in [0,1)$ .

Consider:  $\left\|T(H(\psi)_1) - T(H(\psi)_2)\right\|_{\infty}$ 

$$
= \sup_{\psi \in [0,b]} |(H(\psi)_{1} - (H(\psi)_{2})| + \sup_{\psi \in [0,b]} |(H(\psi)_{2}) - (H(\psi)_{1})| + \sup_{\psi \in [0,b]} |(H(\psi)_{1} - H(\psi)_{2})| \leq \sup_{\psi \in [0,b]} |(H_{1}(g) - H_{2}(g)) \cdot e^{\frac{-g}{\beta \lambda_{1} \lambda_{2}}} ds|
$$
\n
$$
= \sup_{\psi \in [0,b]} |(H(\psi)_{1} - H(\psi)_{2})|_{\infty} e^{\frac{(1-\lambda_{2})\psi}{\beta \lambda_{1} \lambda_{2}}} \cdot e^{\frac{\lambda_{2}(1-\lambda_{1})\gamma}{\beta \lambda_{1} \lambda_{2}}} \cdot e^{\frac{\lambda_{1}\lambda_{2}(a_{0} - a_{0}c_{1-1} - \cdots - a_{0}c_{1-1})\gamma}{\beta}} \left(1 - e^{\frac{-b}{\beta \lambda_{1} \lambda_{2}}}\right)
$$
\n
$$
\leq \sup_{\psi \in [0,b]} ||H(\psi)_{1} - H(\psi)_{2}||_{\infty} e^{\frac{(1-\lambda_{2})\psi}{\beta \lambda_{1} \lambda_{2}}} \cdot e^{\frac{\lambda_{1}\lambda_{2}(a_{0} - a_{0}c_{1-1} - \cdots - a_{0}c_{1-1})\gamma}{\beta}} \left(1 - e^{\frac{-b}{\beta \lambda_{1} \lambda_{2}}}\right)
$$
\n
$$
\leq \lim_{\psi \in [0,b]} ||H(\psi)_{1} - H(\psi)_{2}||_{\infty} e^{\frac{(1-\lambda_{2})\psi}{\beta \lambda_{1} \lambda_{2}}} \cdot e^{\frac{\lambda_{2}(1-\lambda_{1})\gamma}{\beta \lambda_{1} \lambda_{2}}} \cdot e^{\frac{\lambda_{1}\lambda_{2}(a_{0} - a_{0}c_{1-1} - \cdots - a_{0}c_{1-1})\gamma}{\beta}} \cdot e^{\frac{\lambda_{1}\lambda_{2}(a_{0} - a_{0}c_{1-1} - \cdots - a_{0}c_{1-1})\gamma}{\beta \lambda_{1} \lambda_{2}}} \cdot e^{\frac{-b}{\beta \lambda_{1} \lambda_{2}}}
$$
\nMin

$$
= \left\| H(\psi)_1 - H(\psi)_2 \right\|_{\infty} \sup_{\psi \in [0,b]} \left| e^{\frac{(1-\lambda_2)\psi}{\beta \lambda_1 \lambda_2}} \cdot e^{\frac{\lambda_2(1-\lambda_1)\gamma}{\beta \lambda_1 \lambda_2}} \cdot e^{\frac{\lambda_1 \lambda_2 (\theta_0 - \theta_1 \zeta_{1-L} - \cdots - \theta_0 \zeta_{1-\rho L})}{\beta}} \right|
$$

$$
\cdot \left| 1 - e^{\frac{-b}{\beta \lambda_1 \lambda_2}} \right|
$$

 $\leq s \| H(\psi)_1 - H(\psi)_2 \|_{\infty}$ 

in which

$$
s = \sup_{\psi \in [0,b]} \left| e^{\frac{(1-\lambda_2)\psi}{\beta \lambda_1 \lambda_2}} \cdot e^{\frac{\lambda_2(1-\lambda_1)\gamma}{\beta \lambda_1 \lambda_2}} \cdot e^{\frac{\lambda_1 \lambda_2 (\theta_0 - \theta_1 \zeta_{1-L} - \theta_2 \zeta_{1-2L} - \dots - \theta_0 \zeta_{1-\theta L})}{\beta}} \right|
$$
  
 
$$
\times \left| 1 - e^{\frac{-b}{\beta \lambda_1 \lambda_2}} \right|; \quad s \in [0,1).
$$

This study evaluates the results acquired for  $ARL<sub>0</sub>$  and  $ARL<sub>1</sub>$  by employing explicit formulations and the NIE method to involve the  $SMA(O)<sub>L</sub>$  process run on the DEWMA control chart. Comparing the accuracy of the ARL to the

percentage accuracy that can be derived from  
\n%*Accuracy* = 100 - 
$$
\left| \frac{S(\psi) - \tilde{S}(\psi)}{S(\psi)} \right| \times 100\%
$$
.

Plus, performance metrics including the SDRL and MRL are employed to evaluate the efficacy of control charts, [19]. Following are the computations of the SDRL and MRL values for the in-control process.

$$
ARL_0 = \frac{1}{\beta}, SDRL_0 = \sqrt{\frac{1-\beta}{\beta^2}}, MRL_0 = \frac{\log(0.5)}{\log(1-\beta)}, \quad (12)
$$

where  $\beta$  represents a type I error. The current study determined the value of ARL0 to be 370. To determine ARL0, apply Eq. (12) to SDRL0 and MRL0 at approximations 370 and 256, respectively. On the contrary, SDRL1 and MRL1 are calculated by substituting  $\rho$  for  $\beta$ , where  $\rho$ represents a type II error. The enhanced capability to detect shifts in the process mean is indicated by the minimum values of the ARL1, SDRL1, and MRL1.A comparison of the control charts' performances was conducted utilizing the relative mean index (RMI), [20]. For a given scenario, the control chart that exhibits the highest performance has the lowest ARL and RMI values. RMI is calculated as

$$
RMI = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{ARL_{shift,i} - Min[ARL_{shift,i}]}{Min[ARL_{shift,i}]} \right)
$$

 $Min[ARL<sub>shift,i</sub>]$  represents the smallest ARL at the same level of shift for all of the control charts, while *ARL*<sub>*shift,i*</sub> represents the ARL of the control chart corresponding to the shift size of row *i*.

Likewise, metrics for performance can be employed to evaluate the efficacy of a control chart such as the average additional quadratic loss (AEQL), the Performance Comparison Index (PCI). AEQL can be calculated as follows, [21],

$$
AEOL = \frac{1}{\Delta} \sum_{\delta_i = \delta_{\min}}^{\delta_{\max}} (\delta_i^2 \times ARL(\delta_i))
$$
\n(13)

where  $\delta$  represents the specific change in the process, and  $\Delta$  represents the aggregate of number of divisions from  $\delta_{\min}$  to  $\delta_{\max}$ . In this study,  $\Delta = 9$ is determined from  $\delta_{\min} = 0.001$  to  $\delta_{\max} = 0.10$ . with the lowest AEQL value, a control chart is considered to be the most effective.

The PCI value is determined by dividing the AEQL of the control chart by that of the control chart with the lowest AEQL, which represents the control chart with the highest level of effectiveness. The mathematical representation of the PCI is as an expression.

$$
PCI = \frac{AEQL}{AEOL_{lowest}}
$$
 (14)

### **4 Numerical Results**

The accuracy measurements for ARL as determined by explicit formulas and the numerical integral equation method in the comparative study are presented in Table 1 and Table 2 in Appendix. The in-control  $\beta_0 = 1$ , out-of-control process  $\beta_1 = (1+\delta)\beta_0$ , shift sizes ( $\delta$ ) = 0.001, 0.003, 0.005, 0.01, 0.03, 0.05, and  $0.10, ARL_0 = 370$ . The ARL of explicit formulas and NIE method with SMA(2)<sub>4</sub> process for different choices of  $\lambda_1$  with  $\lambda_2 = 0.10 \ \theta_0 = 1$  is presented in Table 1 (Appendix). Table 2 (Appendix) shows the ARL of explicit formulas and NIE method with  $SMA(3)_{12}$  process for different choices of  $\lambda_1$  with  $\lambda_2 = 0.10 \theta_0 = 1$  The results from The ARLs of both approaches are remarkably comparable with a 100% accuracy rate, as demonstrated in Table 1 and Table 2 in Appendix. Moreover, the explicit formula requires a CPU time of approximately 0.1 seconds, a significant decrease in comparison to the NIE method. Furthermore, an analysis of the efficacy of the EWMA and DEWMA control charts was presented. The explicit formulations were employed to assess the ARL outcomes through the  $\lambda_1$  of the values 0.1 and 0.2 on the DEWMA control chart while maintaining the exponential smoothing parameter at 1. The values obtained for  $SMA(2)<sub>4</sub>$  and  $SMA(3)<sub>12</sub>$  are correspondingly displayed in Table 3 and Table 4 in Appendix. In all cases, the ARL of the DEWMA control chart is

significantly lower than that of the EWMA control chart. Furthermore, it is observed that the MRL and SDRL outcomes correspond with the ARL. Particularly, the DEWMA control chart displays the lowest MRL and SDRL values at all shift levels when  $\lambda_1$  is set to 0.10. Consequently, the DEWMA control chart exhibits superior efficacy in comparison to the EWMA control chart.

### **4.1 Application**

In this section, the dataset of monthly WTI oil price from January 2016 to December 2022 is studied to determine the performance of the explicit formula for ARL on the DEWMA control chart and compare the performance with the EWMA control chart. Initially, we started by finding a model for WTI oil price and estimating parameters using maximum likelihood. The data has proved that it is a  $SMA(Q)<sub>L</sub>$  model. The estimated parameters are as follows:  $\theta_1 = 0.951$ , and the in-control parameter of exponential white noise equal to 26.1741, as shown in Table 5 (Appendix). By employing the parameters of this predictive model, it is able to illustrate the following:  $\hat{Y}_t = -0.951 \zeta_{t-12}$ 

The explicit formula method is employed to compare the efficacy of the  $SMA(1)<sub>12</sub>$  model's ARL values on the DEWMA and EWMA control charts with respect to ARL, SDRL, and MRL. The findings are simply presented in Table 6 (Appendix). It is apparent that the results correspond with the information presented in Table 3 and Table 4 in Appendix. According to the results presented in Table 6 and Figure 1 (Appendix), for  $ARL<sub>0</sub>=370$  and 500, the DEWMA control chart when  $\lambda_1 = 0.1$  exhibits the least RMI and AEQL across all levels. Likewise, the PCI of the DEWMA control chart is 1. In addition, the DEWMA (*Dt*) statistics with  $\lambda_1 = 0.05$   $\lambda_2 = 0.10$  for the WTI oil price dataset fitted to  $SMA(1)_{12}$  model are presented in Figure 2 (Appendix). The results indicate that the DEWMA chart can detect a shift at the  $5<sup>th</sup>$ observation. In brief, practical applications involving the utilization of the DEWMA control chart to identify variations in the process consistently demonstrate the efficacy of the explicit formula approach.

### **5 Conclusion**

The explicit ARL formula for the SMA  $(Q)_L$  model on DEWMA control charts is investigated in this study. The explicit formula is accurate and reduces processing time. When comparing the ARL using

percentage accuracy criteria between the explicit formula and the numerical integral equation (NIE) method, the research found that the ARL value was not significantly different. Moreover, considering the effectiveness of DEWMA and EWMA control charts for detecting changes in process mean, the results indicate that the DEWMA control chart shows superior performance compared to the EWMA control chart. Moreover, when considering the RMI, AEQL, and PCI criteria for the DEWMA control chart, the RMI and AEQL values are the lowest as well as the PCI value of 1. In addition, the study found that the results from the model with known parameters and the results from real data with approximated parameters were consistent, i.e., the DEWMA control chart gave the best performance. In future research, the ARL explicit formulas on DEWMA control charts can also be developed for other interesting models, and the integral equation method can be applied to express the formula for average run length values on other types of control charts.

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#### **Declaration of Generative AI and AI-assisted Technologies in the Writing Process**

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### **Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)**

- Rapin Sunthornwat has organized the conceptualization and simulation.
- Yupaporn Areepong has organized the conceptualization, writing-original draft and validation
- Saowanit Sukparungsee has implemented the methodology,software, and validation.

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#### **Conflicts of Interest**

The authors declare no conflict of interest.

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## **APPENDIX**

### Table 1. ARL of explicit formulas and NIE method with  $SMA(2)_4$  process for different choices of  $\lambda_1$  with  $\lambda_2 = 0.10 \ \theta_0 = 1, ARL_0 = 370$



*Note: The numerical results in parentheses are computational times in seconds.* 





*Note: The numerical results in parentheses are computational times in seconds*



Table 3. The ARL of DEWMA control chart for SMA(2)<sup>4</sup> using explicit formula against EWMA control chart given  $\lambda_2 = 0.2$ 

$\theta_0 = 1, \theta_1 = 0.1, \theta_2 = 0.2$ and $\beta_0 = 1$ .										
		$\theta_{1} = 0.2$ $\theta_{\rm s}=0.1$				$\theta_{3} = 0.3$				
	Control	<b>DEWMA</b>	<b>DEWMA</b>	<b>EWMA</b>	<b>DEWMA</b>	<b>DEWMA</b>	<b>EWMA</b>	<b>DEWMA</b>	<b>DEWMA</b>	<b>EWMA</b>
$\delta$	Chart	$\lambda_1 = 0.1$	$\lambda_1 = 0.2$	$\lambda_1 = 1$	$\lambda_1 = 0.1$	$\lambda_1 = 0.2$	$\lambda_1 = 1$	$\lambda_1 = 0.1$	$\lambda_1 = 0.2$	$\lambda_1 = 1$
	<b>UCL</b>	0.02002024	0.00670642	0.0504501	0.00182621	0.00605838	0.0455371	0.001650965	0.0054738	0.0411125
0.00	ARL <sub>0</sub>	370.03400	370.07300	370.22900	370.51700	370.73600	370.60500	370.49600	370.66900	370.92400
	$SDRL_0$	369.53370	369.57270	369.72870	370.01670	370.23570	370.10470	369.99570	370.16870	370.42370
	$MRL_0$	256.14130	256.16830	256.27650	256.47610	256.62790	256.53710	256.46150	256.58140	256.75820
0.001	ARL <sub>1</sub>	163.72400	176.70300	188.41400	161.41000	174.12200	185.46700	159.05600	171.44400	182.58500
	$SDRL_1$	163.22320	176.20230	187.91330	160.90920	173.62130	184.96630	158.55520	170.94330	182.08430
	$MRL_1$	113.13790	122.13430	130.25180	111.53400	120.34530	128.20900	109.90230	118.48900	126.21140
0.003	ARL <sub>1</sub>	77.73330	86.73170	95.38080	76.15040	84.82340	93.10100	74.60320	82.95170	90.91580
	$SDRL_1$	77.23168	86.23025	94.87948	75.64875	84.32192	92.59965	74.10151	82.45018	90.41442
	$MRL_1$	53.53330	59.77059	65.76575	52.43610	58.44784	64.18550	51.36364	57.15046	62.67082
0.005	ARL <sub>1</sub>	51.15130	57.65970	64.04660	50.01480	56.25770	62.34250	48.91420	54.89990	60.71930
	$SDRL_1$	50.64883	57.15751	63.54463	49.51228	55.75546	61.84048	48.41162	54.39760	60.21722
	$MRL_1$	35.10767	39.61907	44.04624	34.31988	38.64726	42.86502	33.55697	37.70608	41.73988
0.007	ARL <sub>1</sub>	38.21910	43.29020	48.31820	37.33720	42.18980	46.96900	36.48660	41.13040	45.68780
	$SDRL_1$	37.71579	42.78728	47.81559	36.83381	41.68680	46.46631	35.98313	40.62732	45.18503
	$MRL_1$	26.14336	29.65856	33.14384	25.53203	28.89578	32.20861	24.94241	28.16143	31.32052
0.01	ARL <sub>1</sub>	27.81030	31.61480	35.41910	27.15090	30.78450	34.39360	26.51710	29.98870	33.42220
	$SDRL_1$	27.30572	31.11078	34.91552	26.64621	30.28037	33.88991	26.01230	29.48446	32.91840
	MRL <sub>1</sub>	18.92794	21.56528	24.20242	18.47083	20.98971	23.49155	18.03146	20.43805	22.81818
0.03	ARL <sub>1</sub>	10.25730	11.69930	13.16380	10.00910	11.38150	12.76590	9.77180	11.07920	12.39070
	$SDRL_1$	9.74448	11.18813	12.65393	9.49595	10.87001	12.25570	9.25831	10.56738	11.88018
	$MRL_1$	6.75732	7.75760	8.77331	6.58513	7.53717	8.49736	6.42049	7.32748	8.23715
0.05	ARL <sub>1</sub>	6.53155	7.43379	8.35432	6.37661	7.23445	8.10371	6.22868	7.04515	7.86767
	$SDRL_1$	6.01079	6.91574	7.83839	5.85530	6.71586	7.58725	5.70682	6.52602	7.35068
	$MRL_1$	4.17116	4.79780	5.43684	4.06351	4.65938	5.26289	3.96072	4.52791	5.09903
0.07	ARL <sub>1</sub>	4.91324	5.57601	6.25414	4.79960	5.42936	6.06931	4.69121	5.29024	5.89536
	$SDRL_1$	4.38483	5.05132	5.73238	4.27043	4.90394	5.54682	4.16128	4.76407	5.37214
	MRL <sub>1</sub>	3.04589	3.50701	3.97841	2.96677	3.40502	3.84996	2.89129	3.30825	3.72905
0.10	ARL <sub>1</sub>	3.69272	4.17205	4.66413	3.61071	4.06582	4.52985	3.53254	3.96514	4.40356
	$SDRL_1$	3.15333	3.63785	4.13400	3.07026	3.53059	3.99871	2.99104	3.42888	3.87141
	$MRL_1$	2.19481	2.52946	2.87243	2.13748	2.45535	2.77889	2.08281	2.38509	2.69088
<b>RMI</b>		$\bf{0}$	0.1261	0.2517	$\bf{0}$	0.1233	0.2453	$\bf{0}$	0.1205	0.2394
<b>AEQL</b>		0.0103	0.0117	0.0131	0.0101	0.0114	0.0127	0.0099	0.0111	0.0124
<b>PCL</b>		$\mathbf{1}$	1.1336	1.2701	1	1.1301	1.2619	$\mathbf{1}$	1.1266	1.2542

Table 4. The ARL of DEWMA control chart for SMA(3)<sub>12</sub> using explicit formula against EWMA control chart given  $\lambda_2 = 0.2$ 

Table 5. The coefficients for the  $SMA(1)<sub>12</sub>$  model using the real-world dataset.

model		SMA(1) <sub>12</sub>			
parameters		<b>SE</b>	p-value		
SMA(1)	0.951	0.036	0.000		
<b>RMSE</b>		27.372			
Normalized BIC		6.672			
<b>Residual</b>		<b>Residual of SMA(1) model</b>			
Exponential parameter		26.1741			
One-sample					
Kolmogorov-Smirnov test		1.343			
p-value	0.054				



### Table 6. The ARL of DEWMA control chart for SMA(1)<sub>12</sub> using explicit formula against EWMA control chart given  $\lambda_2 = 0.2$







(b)



(c)

Fig. 1: Comparison the RMI, AEQL and PCI values among DEWMA and EWMA control charts



Fig. 2: The dataset fitted to SMA(1)<sub>12</sub> process running on DEWMA control chart when  $\lambda_1 = 0.05$ ,  $\lambda_2 = 0.1$