MIXED AND ADAPTIVE MEMORY CONTROL CHARTS FOR PROCESS MONITORING

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ABSTRACT

Control charts are statistical tools widely used to monitor changes in the parameters of production processes. The most popular control charts in practice are Shewhart, cumulative sum (CUSUM) and exponentially weighted moving average (EWMA). The Shewhart control chart is considered sensitive to detect large shifts, whereas both the CUSUM and EWMA control charts are used to detect small-to-moderate shifts in a process location. To monitor both the small and large shifts simultaneously through a single control chart, several adaptive control charts have been suggested in the literature. However, most adaptive control charts approaches were designed only to monitor the process location. Thus improvements on the design structures of such control charts form the basis of this research. This study aims to develop adaptive control charts based on Huber and Bi-square functions as well as mixed control charts for efficient monitoring of the process location and dispersion parameters. The proposal includes the adaptive EWMA based on EWMA statistic, adaptive EWMA based on CUSUM statistic, and adaptive CUSUM based on CUSUM statistic. The other proposed charts are the mixed EWMA-CUSUM control chart to simultaneously monitor the process location and dispersion; and the mixed CUSUM-EWMA control charts for monitoring the dispersion of a process. There is also a multivariate extension of mixed CUSUM-EWMA which combines the design structures of the multivariate CUSUM and EWMA control charts. The statistical performances of the proposed control charts are evaluated using different performance measures. These performance measures include the average run length, standard deviation run length, extra quadratic loss, relative average run length, and performance comparison index. The results show that the proposed control charts are very effective in detecting wide range of shifts in the process locations and dispersion parameters. The graphical displays of statistical plots and operating curves show that the proposed charts significantly outperform most of the existing control charts. Interestingly, some existing control charts are special cases of the proposed control charts. Illustrative examples using real-life data are also given to demonstrate the practical importance and procedural details of the proposed methods.

ABSTRAK

Carta kawalan adalah alat statistik yang digunakan secara meluas untuk memantau perubahan parameter proses penghasilan. Carta kawalan paling popular yang masih dipraktikkan ialah Shewhart, jumlah kumulatif (CUSUM) dan purata bergerak berwajaran exponen (EWMA). Carta kawalan Shewmart dikira sensitif bagi mengesan anjakan yang besar, manakala carta kawalan CUSUM dan EWMA digunakan untuk mengesan anjakan kecil hingga sederhana bagi proses lokasi. Untuk memantau kedua-dua anjakan besar dan kecil secara serentak melalui carta kawalan tunggal, beberapa carta kawalan penyesuaian telah dicadangkan dalam literatur. Namun, kebanyakan pendekatan dengan penyesuaian ini telah dicipta hanya untuk memantau proses lokasi. Justeru, penambahbaikan pada struktur reka bentuk carta kawalan tersebut menjadi asas bagi penyelidikan ini. Kajian ini bertujuan untuk membangunkan carta kawalan penyesuaian berdasarkan fungsi Huber dan Bi-square serta carta kawalan campuran untuk pemantauan parameter proses lokasi dan penyebaran yang cekap. Cadangan tersebut merangkumi EWMA penyesuaian berdasarkan statistik EWMA, EWMA penyesuaian berdasarkan statistik CUSUM, dan CUSUM penyesuaian berdasarkan statistik CUSUM. Cadangan carta kawalan lain adalah carta kawalan campuran EWMA-CUSUM untuk memantau proses lokasi dan penyebaran secara serentak; dan carta kawalan campuran CUSUM-EWMA untuk memantau penyebaran sesuatu proses. Terdapat juga sambungan multivariat bagi campuran CUSUM-EWMA yang menggabungkan struktur reka bentuk carta kawalan multivariat CUSUM dan EWMA. Prestasi statistik bagi cadangan carta kawalan tersebut telah dinilai menggunakan pengukur prestasi yang berbeza-beza. Pengukur prestasi itu termasuk purata panjang kendalian, sisihan piawai panjang kendalian, kehilangan kuadratik tambahan, purata relatif panjang kendalian, dan indeks perbandingan prestasi. Hasil kajian menunjukkan bahawa cadangan tersebut sangat efektif dalam mengesan peralihan dalam julat yang luas bagi parameter proses lokasi dan penyebaran. Paparan grafik plot statistik dan lengkung panjang kendalian menunjukkan bahawa carta yang dicadangkan mengatasi dengan signifikan kebanyakan carta kawalan yang wujud. Menariknya, beberapa carta kawalan yang wujud adalah kes khas daripada carta kawalan yang dicadangkan. Contoh gambaran menggunakan data nyata turut disertakan untuk menunjukkan kepentingan praktikal dan perincian prosedur bagi kaedah-kaedah yang dicadangkan.

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LIST OF ABBREVIATIONS

AEWMA	-	Adaptive exponentially weighted moving average
ACUSUM	-	Adaptive cumulative sum
ARL	-	Average run length
CDF		Cumulative distribution function
CMEC		Combined Mixed EWMA-CUSUM
CMDEC		Combined double Mixed EWMA-CUSUM
CL	-	Centre line
CUSUM	-	Cumulative sum
DEWMA	-	Double exponentially weighted moving average
EQL	-	Extra quadratic loss
EWMA	-	Exponentially weighted moving average
FIR	-	Fast initial response
HEWMA	-	Hybrid EWMA
LCL	-	Lower control limit
Max CUSUM	-	Maximum CUSUM
MaxEWMA	-	Maximum EWMA
MaxDEWMA	-	Maximum double EWMA
MaxGEWMA	-	Maximum generally EWMA
MCE	-	Mixed CUSUM-EWMA
MD	-	Mahalanobis distance
MCUSUM	-	Multivariate CUSUM
MEC	-	Mixed EWMA-CUSUM
MEWMA	-	Multivariate EWMA
ML	-	Mean Value
NEWMA	-	New EWMA
ODRS	-	Ordered double ranked set sampling
OIDRSS	-	Ordered imperfect double rank set sampling
PCA	-	Principle component analysis
PC-chart	-	Principle component control chart
PCI	-	Performance comparison index

PV	-	Progressive variance
RL	-	Run length
RARL		Relative average run length
SDRL	-	Standard deviation of run length
SERL		Standard rrror of run length
SPC	-	Statistical process control
UCL	-	Upper control limit
VSI	-	Variable sampling interval
VSIFT	-	VSI fixed time
VSI-WLF	-	VSI and weight loss function
VSS	-	Variable sample size
VSSI	-	VSS and sampling intervals
VSS-AEWMA	-	Variable sample size AEWMA
VSSI-WLF	-	VSSI and weight loss function
WLF	-	Weight loss function
W & N	-	Woodall and Ncube control chart

LIST OF NOTATIONS

$A_T(n)$	-	Constant of T_i transformation
a_T	-	Constant of T_i transformation
A_J	-	Constant of J_i transformation
a_J	-	Constant of J_i transformation
a'_p	-	Eigenvalues
CUSUM-S^2	-	CUSUM control chart for process dispersion
$\mathrm{ACUSUM_C}$	-	Adaptive CUSUM control charts for process location based on classical CUSUM statistic
$\mathrm{ACUSUM_E}$	-	Adaptive CUSUM control chart for process location based on classical EWMA statistic
$\mathrm{ACUSUM_C^{(1)}}$	-	$\mathrm{ACUSUM_C}$ control chart based on Huber function
$ACUSUM_{Ci}^{(1)\pm}$	-	Plotting statistics of $\mathrm{ACUSUM_C^{(1)}}$ control chart
$\mathrm{ACUSUM_C^{(2)}}$	-	$\mathrm{ACUSUM_C}$ control chart based on Bi-square function
$ACUSUM_{Ci}^{(2)\pm}$	-	Plotting statistics of $\mathrm{ACUSUM_C^{(2)}}$ control chart
$\mathrm{AEWMA_C}$	-	Adaptive EWMA control charts for process location based on CUSUM statistic
$\mathrm{AEWMA_E}$	-	Adaptive EWMA control charts for process location based on classical EWMA statistic
$\mathrm{AEWMA_C^{(1)}}$	-	$\mathrm{AEWMA_C}$ control chart based on Huber function
$AEWMA_{ci}^{(1)}$	-	Plotting statistic of $\mathrm{AEWMA_C^{(1)}}$ control chart
$\mathrm{AEWMA_C^{(2)}}$	-	$\mathrm{AEWMA_C}$ control chart based on Bi-square function
$AEWMA_{ci}^{(2)}$	-	Plotting statistic of $\mathrm{AEWMA_C^{(2)}}$ control chart
$\mathrm{AEWMAF_C}$	-	Adaptive EWMA control charts for process dispersion based on CUSUM statistic
$\mathrm{AEWMAF_C^{(1)}}$	-	$\mathrm{AEWMAF_C}$ control chart based on Huber function
$AEWMAF_{ci}^{(1)}$	-	Plotting statistic of $\mathrm{AEWMAF_C^{(1)}}$ control chart
$AEWMAT_{c\,i}^{(1)}$	-	Plotting statistic of $\mathrm{AEWMAT_C^{(1)}}$ control chart

$AEWMAJ_{c\,i}^{(1)}$	-	Plotting statistic of $\mathrm{AEWMAJ}_{\mathrm{C}}^{(1)}$ control chart
$\mathrm{AEWMAF}_{\mathrm{C}}^{(2)}$	-	$\mathrm{AEWMAF}_{\mathrm{C}}$ control chart based on Bi-square function
$AEWMAF_{ci}^{(2)}$	-	Plotting statistic of $\mathrm{AEWMAF}_{\mathrm{C}}^{(2)}$ control chart
$AEWMAT_{c\,i}^{(2)}$	-	Plotting statistic of $\mathrm{AEWMAT}_{\mathrm{C}}^{(2)}$ control chart
$AEWMAJ_{c\,i}^{(2)}$	-	Plotting statistic of $\mathrm{AEWMAF}_{\mathrm{C}}^{(2)}$ control chart
$\mathrm{AEWMAF}_{\mathrm{E}}$	-	Adaptive EWMA control charts for process dispersion based on EWMA statistic
$\mathrm{AEWMAF}_{\mathrm{E}}^{(1)}$	-	$\mathrm{AEWMAF}_{\mathrm{E}}$ control chart based on Huber function
$AEWMAT_{E\,i}^{(1)}$	-	Plotting statistic of $\mathrm{AEWMAT}_{\mathrm{E}}^{(1)}$ control chart
$AEWMAJ_{E\,i}^{(1)}$	-	Plotting statistic of $\mathrm{AEWMAJ}_{\mathrm{E}}^{(1)}$ control chart
$AEWMAV_{E\,i}^{(1)}$	-	Plotting statistic of $\mathrm{AEWMAV}_{\mathrm{E}}^{(1)}$ control chart
$\mathrm{AEWMAF}_{\mathrm{E}}^{(2)}$	-	$\mathrm{AEWMAF}_{\mathrm{E}}$ control chart based on Bi-square function
$AEWMAT_{E\,i}^{(2)}$	-	Plotting statistic of $\mathrm{AEWMAT}_{\mathrm{E}}^{(2)}$ control chart
$AEWMAJ_{E\,i}^{(2)}$	-	Plotting statistic of $\mathrm{AEWMAJ}_{\mathrm{E}}^{(2)}$ control chart
$AEWMAV_{E\,i}^{(2)}$	-	Plotting statistic of $\mathrm{AEWMAV}_{\mathrm{E}}^{(2)}$ control chart
$ARL(\delta)$	-	ARL at specific shift
$ARL_{(\delta_{(l)})}$	-	ARL of a specific control chart at specific shift
$ARL_{\,min(\delta_{(l)})}$	-	Smallest ARL from all control charts
$ARL_{\,min(\delta)}$	-	Smallest ARL from all control charts
$\mathrm{ARL}_{\mathrm{bmk}(\delta)}$	-	ARL of benchmark control chart
ARL_0	-	In-control average run length
ARL_1	-	Out-of-control average run length
$B_T(n)$	-	Constant of T_i transformation
b_T	-	Constant of T_i transformation
B_J	-	Constant of J_i transformation
b_J	-	Constant of J_i transformation
$C_T(n)$	-	Constant of T_i transformation
c_t	-	Constant of T_i transformation
C_J	-	Constant of J_i transformation
c_J	-	Constant of J_i transformation

C_i	-	Observations vector of MCUSUM control chart
C_i^1	-	Observations vector of $\mathrm{MC}^{(1)}$ control chart
$CL_{\mathrm{EWMA}i}$	-	CL of classical EWMA control chart
$CL_{\mathrm{EWMAF}i}$	-	CL of EWMAF control chart
$CL_{\mathrm{EWMAT}i}$	-	CL of EWMAT control chart
CL_{EWMA}	-	Constant CL of classical EWMA control chart
$CL_{AEWMA_{ci}^{(2)}}$	-	CL of $\mathrm{AEWMA}_{\mathrm{C}}^{(2)}$ control chart
$CL_{AEWMAF_{ci}^{(1)}}$	-	CL of $\mathrm{AEWMAF}_{\mathrm{C}}^{(1)}$ control charts
$CL_{AEWMAT_{ci}^{(1)}}$	-	CL of $\mathrm{AEWMAT}_{\mathrm{C}}^{(1)}$ control chart
$CL_{AEWMAJ_{ci}^{(1)}}$	-	CL of $\mathrm{AEWMAJ}_{\mathrm{C}}^{(1)}$ control chart
$CL_{AEWMAF_{ci}^{(2)}}$	-	CL of $\mathrm{AEWMAF}_{\mathrm{C}}^{(2)}$ control charts
$CL_{AEWMAT_{ci}^{(2)}}$	-	CL of $\mathrm{AEWMAT}_{\mathrm{C}}^{(2)}$ control chart
$CL_{AEWMAJ_{ci}^{(2)}}$	-	CL of $\mathrm{AEWMAJ}_{\mathrm{C}}^{(2)}$ control chart
$CL_{AEWMAF_{Ei}^{(1)}}$	-	CL of $\mathrm{AEWMAF}_{\mathrm{E}}^{(1)}$ control charts
$CL_{AEWMAT_{Ei}^{(1)}}$	-	CL of $\mathrm{AEWMAT}_{\mathrm{E}}^{(1)}$ control chart
$CL_{AEWMAJ_{Ei}^{(1)}}$	-	CL of $\mathrm{AEWMAJ}_{\mathrm{E}}^{(1)}$ control chart
$CL_{AEWMAV_{Ei}^{(1)}}$	-	CL of $\mathrm{AEWMAV}_{\mathrm{E}}^{(1)}$ control chart
$CL_{AEWMAF_{Ei}^{(2)}}$	-	CL of $\mathrm{AEWMAF}_{\mathrm{E}}^{(2)}$ control charts
$CL_{AEWMAT_{Ei}^{(2)}}$	-	CL of $\mathrm{AEWMAT}_{\mathrm{E}}^{(2)}$ control chart
$CL_{AEWMAJ_{Ei}^{(2)}}$	-	CL of $\mathrm{AEWMAJ}_{\mathrm{E}}^{(2)}$ control chart
$CL_{AEWMAV_{Ei}^{(2)}}$	-	CL of $\mathrm{AEWMAV}_{\mathrm{E}}^{(2)}$ control chart
$\mathrm{CMECU}_i^{\pm}$	-	Plotting statistics of CMEC control chart
$\mathrm{CMECV}_i^{\pm}$	-	Plotting statistics of CMEC control chart
$\mathrm{CMDECU}_i^{\pm}$	-	Plotting statistics of CMDEC control chart
$\mathrm{CMDECV}_i^{\pm}$	-	Plotting statistics of CMDEC control chart
$CUSUM_i^{\pm}$	-	Plotting statistics of classical CUSUM control chart
$CUSUMF_i^{\pm}$	-	Plotting statistics of CUSUMF control charts
$CUSUMT_i^{\pm}$	-	Plotting statistics of CUSUMT control chart

$CUSUMU_i^{\pm}$	-	Statistics for Max CUSUM control chart
$CUSUMV_i^{\pm}$	-	Statistics for Max CUSUM control chart
D_i	-	Standardized statistic for the $\mathrm{AEWMAF_E}$ control charts
D_J	-	Constant of J_i transformation
d_J	-	Constant of J_i transformation
E_i	-	Observations vector for MEWMA control chart
$EWMA_i$	-	Plotting statistic of classical EWMA control chart
$EWMAF_i$	-	Plotting statistic of EWMAF control charts
$EWMAT_i$	-	Plotting statistic of the EWMAT control chart
EWMAU_i	-	Statistic for MaxEWMA control chart
EWMAV_i	-	Statistic for MaxEWMA control chart
EWMADU_i	-	Statistic for MaxDEWMA control chart
EWMADV_i	-	Statistic for MaxDEWMA control chart
$\mathrm{EQL}_{\text{best chart}}$	-	EQL of the best performing control chart
F_i	-	Represents T_i, J_i, and V_i tranformations
h	-	Control limit coefficient of classical CUSUM control chart
H	-	UCL of classical CUSUM control chart
$\mathrm{h_F}$	-	Control limit coefficient of CUSUMF control charts
$\mathrm{H_F}$	-	UCL of CUSUMF control charts
$\mathrm{h_T}$	-	Control limit coefficient of CUSUMT control chart
$\mathrm{H_T}$	-	UCL of CUSUMT control chart
$\mathrm{H_{MaxCUSUM}}$	-	UCL of Max CUSUM control chart
$\mathrm{H_{MC}}$	-	UCL of MCUSUM control chart
$\mathrm{H_{ME}}$	-	UCL of MEWMA control chart
$\mathrm{h}_{\mathrm{ACUSUM}_\mathrm{C}^{(1)}}$	-	Control limit coefficient of $\mathrm{ACUSUM}_\mathrm{C}^{(1)}$ control chart
$\mathrm{H}_{\mathrm{ACUSUM}_\mathrm{C}^{(1)}}$	-	UCL of $\mathrm{ACUSUM}_\mathrm{C}^{(1)}$ control chart
$\mathrm{h}_{\mathrm{ACUSUM}_\mathrm{C}^{(2)}}$	-	Control limit coefficient of $\mathrm{ACUSUM}_\mathrm{C}^{(2)}$ control chart
$\mathrm{H}_{\mathrm{ACUSUM}_\mathrm{C}^{(2)}}$	-	UCL of $\mathrm{ACUSUM}_\mathrm{C}^{(2)}$ control chart
$\mathrm{h_{CMEC}}$	-	Control limit coefficient of CMEC control chart
H_{CMECi}	-	Time-varying control limit of CMEC control chart

$\mathrm{h}_{\mathrm{CMDEC}}$	-	Control limit coefficient of CMDEC control chart
H_{CMDECi}	-	Time-varying control limit of CMDEC control chart
$\mathrm{H}_{\mathrm{MC}^{(1)}}$	-	UCL of the $\mathrm{MC}^{(1)}$ control chart
$\mathrm{H}_{\mathrm{MCPC}^{(1)}}$	-	UCL of $\mathrm{MCPC}^{(1)}$ control chart
$\mathrm{H}_{\mathrm{MCE}^{(1)}}$	-	UCL of $\mathrm{MCE}^{(1)}$ control chart
$\mathrm{h}_{\mathrm{MCE}^{(2)}}$	-	Control limit coefficient of $\mathrm{MCE}^{(2)}$ control chart
J_i	-	Four-parameters logarithmic transformation
K/k	-	Constants of classical CUSUM control chart
K_1/k_1	-	Constant of CUSUMF control charts
K_2/k_2	-	Constant of Max CUSUM control chart
k_3	-	Constant of CMEC control chart
K_{3i}	-	Time-varying parameter of CMEC control chart
k_4	-	Constant of CMDEC control chart
K_{4i}	-	Time-varying parameter of CMDEC control chart
K_m/k_m	-	Constant of MCUSUM, $\mathrm{MC}^{(1)}$, $\mathrm{MCPC}^{(1)}$, and $\mathrm{MCE}^{(2)}$ control charts
L	-	Control limit coefficient of classical EWMA control chart
L_{F}	-	Control limit coefficient of EWMAF control charts
L_{T}	-	Control limit coefficient of EWMAT control chart
$\mathrm{L}_{\mathrm{MaxEWMA}}$	-	Control limit coefficient of MaxEWMA control charts
$\mathrm{L}_{\mathrm{MaxDEWMA}}$	-	Control limit coefficient of MaxDEWMA control charts
$\mathrm{L}_{\mathrm{MCEF}}$	-	Control limit coefficient of MCEF control charts
$\mathrm{L}_{\mathrm{MCET}}$	-	Control limit coefficient of MCET control chart
$\mathrm{L}_{\mathrm{MCEJ}}$	-	Control limit coefficient of MCEJ control chart
$\mathrm{L}_{\mathrm{MCEV}}$	-	Control limit coefficient of MCEV control chart
$\mathrm{L}_{\mathrm{AEWMA}_{\mathrm{C}}^{(1)}}$	-	Control limit coefficient of $\mathrm{AEWMA}_{\mathrm{C}}^{(1)}$ control chart
$\mathrm{L}_{\mathrm{AEWMA}_{\mathrm{C}}^{(2)}}$	-	Control limit coefficient of $\mathrm{AEWMA}_{\mathrm{C}}^{(2)}$ control chart
$\mathrm{L}_{\mathrm{AEWMAF}_{\mathrm{C}}^{(1)}}$	-	Control limit coefficient of $\mathrm{AEWMAF}_{\mathrm{C}}^{(1)}$ control chart
$\mathrm{L}_{\mathrm{AEWMAT}_{\mathrm{C}}^{(1)}}$	-	Control limit coefficient of $\mathrm{AEWMAT}_{\mathrm{C}}^{(1)}$ control chart
$\mathrm{L}_{\mathrm{AEWMAJ}_{\mathrm{C}}^{(1)}}$	-	Control limit coefficient of $\mathrm{AEWMAJ}_{\mathrm{C}}^{(1)}$ control chart
$\mathrm{L}_{\mathrm{AEWMAF}_{\mathrm{C}}^{(2)}}$	-	Control limit coefficient of $\mathrm{AEWMAF}_{\mathrm{C}}^{(2)}$ control chart

$\mathrm{L}_{\mathrm{AEWMAT}_{\mathrm{C}}^{(2)}}$ - Control limit coefficient of $\mathrm{AEWMAT}_{\mathrm{C}}^{(2)}$ control chart

$\mathrm{L}_{\mathrm{AEWMAJ}_{\mathrm{C}}^{(2)}}$ - Control limit coefficient of $\mathrm{AEWMAJ}_{\mathrm{C}}^{(2)}$ control chart

$\mathrm{L}_{\mathrm{AEWMAF}_{\mathrm{E}}^{(1)}}$ - Control limit coefficient of $\mathrm{AEWMAF}_{\mathrm{E}}^{(1)}$ control chart

$\mathrm{L}_{\mathrm{AEWMAT}_{\mathrm{E}}^{(1)}}$ - Control limit coefficient of $\mathrm{AEWMAT}_{\mathrm{E}}^{(1)}$ control chart

$\mathrm{L}_{\mathrm{AEWMAJ}_{\mathrm{E}}^{(1)}}$ - Control limit coefficient of $\mathrm{AEWMAJ}_{\mathrm{E}}^{(1)}$ control chart

$\mathrm{L}_{\mathrm{AEWMAV}_{\mathrm{E}}^{(1)}}$ - Control limit coefficient of $\mathrm{AEWMAV}_{\mathrm{E}}^{(1)}$ control chart

$\mathrm{L}_{\mathrm{AEWMAF}_{\mathrm{E}}^{(2)}}$ - Control limit coefficient of $\mathrm{AEWMAF}_{\mathrm{E}}^{(2)}$ control chart

$\mathrm{L}_{\mathrm{AEWMAT}_{\mathrm{E}}^{(2)}}$ - Control limit coefficient of $\mathrm{AEWMAT}_{\mathrm{E}}^{(2)}$ control chart

$\mathrm{L}_{\mathrm{AEWMAJ}_{\mathrm{E}}^{(2)}}$ - Control limit coefficient of $\mathrm{AEWMAJ}_{\mathrm{E}}^{(2)}$ control chart

$\mathrm{L}_{\mathrm{AEWMAV}_{\mathrm{E}}^{(2)}}$ - Control limit coefficient of $\mathrm{AEWMAV}_{\mathrm{E}}^{(2)}$ control chart

$LCL_{\mathrm{EWMA}i}$ - Time-varying LCL of classical EWMA control chart

$LCL_{\mathrm{EWMAF}i}$ - Time-varying LCL of EWMAF control chart

LCL_{EWMA} - Constant LCL of classical EWMA control chart

$LCL_{AEWMA_{ci}^{(1)}}$ - Time-varying LCL of $\mathrm{AEWMA}_{\mathrm{C}}^{(1)}$ control chart

$LCL_{AEWMA_{ci}^{(2)}}$ - Time-varying LCL of $\mathrm{AEWMA}_{\mathrm{C}}^{(2)}$ control chart

$LCL_{AEWMAF_{ci}^{(1)}}$ - Time-varying LCL of $\mathrm{AEWMAF}_{\mathrm{C}}^{(1)}$ control chart

$LCL_{AEWMAT_{ci}^{(1)}}$ - Time-varying LCL of $\mathrm{AEWMAT}_{\mathrm{C}}^{(1)}$ control chart

$LCL_{AEWMAJ_{ci}^{(1)}}$ - Time-varying LCL of $\mathrm{AEWMAJ}_{\mathrm{C}}^{(1)}$ control chart

$LCL_{AEWMAF_{ci}^{(2)}}$ - Time-varying LCL of $\mathrm{AEWMAF}_{\mathrm{C}}^{(2)}$ control chart

$LCL_{AEWMAF_{Ei}^{(1)}}$ - Time-varying LCL of $\mathrm{AEWMAF}_{\mathrm{E}}^{(1)}$ control chart

$LCL_{AEWMAT_{Ei}^{(1)}}$ - Time-varying LCL of $\mathrm{AEWMAT}_{\mathrm{E}}^{(1)}$ control chart

$LCL_{AEWMAJ_{Ei}^{(1)}}$ - Time-varying LCL of $\mathrm{AEWMAJ}_{\mathrm{E}}^{(1)}$ control chart

$LCL_{AEWMAV_{Ei}^{(1)}}$ - Time-varying LCL of $\mathrm{AEWMAV}_{\mathrm{E}}^{(1)}$ control chart

$LCL_{AEWMAF_{Ei}^{(2)}}$ - Time-varying LCL of $\mathrm{AEWMAF}_{\mathrm{E}}^{(2)}$ control chart

$LCL_{AEWMAT_{Ei}^{(2)}}$ - Time-varying LCL of $\mathrm{AEWMAT}_{\mathrm{E}}^{(2)}$ control chart

$LCL_{AEWMAJ_{Ei}^{(2)}}$ - Time-varying LCL of $\mathrm{AEWMAJ}_{\mathrm{E}}^{(2)}$ control chart

$LCL_{AEWMAV_{Ei}^{(2)}}$	-	Time-varying LCL of $\mathrm{AEWMAV_E^{(2)}}$ control chart
$MaxCUSUM_i$	-	Plotting statistic of Max CUSUM control chart
$MaxEWMA_i$	-	Plotting statistic of MaxEWMA control chart
$MaxDEWMA_i$	-	Plotting statistic of MaxDEWMA control chart
$\mathrm{MC}^{(1)}$	-	MCUSUM control chart
MC_i	-	Plotting statistic of MCUSUM control chart
$MC_i^{(1)}$	-	Plotting statistic of $\mathrm{MC}^{(1)}$ control chart
$MCE_i^{(2)}$	-	Plotting statistic of $\mathrm{MCE}^{(2)}$ control chart
$MCE_i^{(1)}$	-	Plotting statistic of $\mathrm{MCE}^{(1)}$ control chart
$MCEF_i^{\pm}$	-	Plotting statistics of MCEF control charts
$MCET_i^{\pm}$	-	Plotting statistics of MCET control chart
$MCEJ_i^{\pm}$	-	Plotting statistics of MCEJ control chart
$MCEV_i^{\pm}$	-	Plotting statistics of MCEV control chart
ME_i	-	Plotting statistic of MEWMA control chart
$MCPC_i^{(1)}$	-	Plotting statistic of $\mathrm{MCPC}^{(1)}$ control chart
PCA_{ci}	-	Input statistic of $\mathrm{MCPC}^{(1)}$ control chart
PCA_i^2	-	Plotting statistic of PC-chart
S_i	-	Observations vector of MCUSUM control chart
S^2-EWMA	-	EWMA control chart for process dispersion
T_i	-	Tranformation for a process dispersion
T_{Hi}^2	-	Plotting statistic of Hotelling's T^2 control chart
$UCL_{\mathrm{EWMA}i}$	-	Time-varying UCL of classical EWMA control chart
$UCL_{\mathrm{EWMAF}i}$	-	Time-varying UCL of EWMAF control chart
$UCL_{\mathrm{EWMAT}i}$	-	Time-varying UCL of EWMAF control chart
UCL_{EWMA}	-	Constant UCL of classical EWMA control chart
$UCL_{MaxEWMAi}$	-	Time-varying UCL of MaxEWMA control chart
$UCL_{MaxDEWMAi}$	-	Time-varying UCL of MaxDEWMA control chart
$UCL_{AEWMA_{ci}^{(1)}}$	-	Time-varying UCL of $\mathrm{AEWMA_C^{(1)}}$ control chart
$UCL_{AEWMA_{ci}^{(2)}}$	-	Time-varying UCL of $\mathrm{AEWMA_C^{(2)}}$ control chart
$UCL_{AEWMAF_{ci}^{(1)}}$	-	Time-varying UCL of $\mathrm{AEWMAF_C^{(1)}}$ control chart

$UCL_{AEWMAT_{ci}^{(1)}}$	-	Time-varying UCL of $\text{AEWMAT}_{\text{C}}^{(1)}$ control chart
$UCL_{AEWMAJ_{ci}^{(1)}}$	-	Time-varying UCL of $\text{AEWMAJ}_{\text{C}}^{(1)}$ control chart
$UCL_{AEWMAF_{ci}^{(2)}}$	-	Time-varying UCL of $\text{AEWMAF}_{\text{C}}^{(2)}$ control chart
$UCL_{AEWMAT_{ci}^{(2)}}$	-	Time-varying UCL of $\text{AEWMAT}_{\text{C}}^{(2)}$ control chart
$UCL_{AEWMAJ_{ci}^{(2)}}$	-	Time-varying UCL of $\text{AEWMAJ}_{\text{C}}^{(2)}$ control chart
$UCL_{AEWMAF_{Ei}^{(1)}}$	-	Time-varying UCL of $\text{AEWMAF}_{\text{E}}^{(1)}$ control chart
$UCL_{AEWMAT_{Ei}^{(1)}}$	-	Time-varying UCL of $\text{AEWMAT}_{\text{E}}^{(1)}$ control chart
$UCL_{AEWMAJ_{Ei}^{(1)}}$	-	Time-varying UCL of $\text{AEWMAJ}_{\text{E}}^{(1)}$ control chart
$UCL_{AEWMAV_{Ei}^{(1)}}$	-	Time-varying UCL of $\text{AEWMAV}_{\text{E}}^{(1)}$ control chart
$UCL_{AEWMAF_{Ei}^{(2)}}$	-	Time-varying UCL of $\text{AEWMAF}_{\text{E}}^{(2)}$ control chart
$UCL_{AEWMAT_{Ei}^{(2)}}$	-	Time-varying UCL of $\text{AEWMAT}_{\text{E}}^{(2)}$ control chart
$UCL_{AEWMAJ_{Ei}^{(2)}}$	-	Time-varying UCL of $\text{AEWMAJ}_{\text{E}}^{(2)}$ control chart
$UCL_{AEWMAV_{Ei}^{(2)}}$	-	Time-varying UCL of $\text{AEWMAV}_{\text{E}}^{(2)}$ control chart
$UCL_{MCE^{(2)}i}$	-	Time-varying UCL of $\text{MCE}^{(2)}$ control chart
UCL_{T^2}	-	Control limit of Hotelling's T^2 control chart
UCL_{PCA}	-	Control limit of PC-chart
U_i	-	Transformation for a process location
V_i	-	Transformation for a process dispersion
$w_1(e_{1i})$	-	Proposed time-varying parameter for $\text{AEWMA}_{\text{C}}^{(1)}$ and $\text{ACUSUM}_{\text{C}}^{(1)}$ control charts
$w_2(e_{1i})$	-	Proposed time-varying parameter for $\text{AEWMA}_{\text{C}}^{(2)}$ and $\text{ACUSUM}_{\text{C}}^{(2)}$ control charts
$w_1(e_{2i})$	-	Proposed time-varying parameter for $\text{AEWMAF}_{\text{C}}^{(1)}$ ($\text{AEWMAT}_{\text{C}}^{(1)}$ and $\text{AEWMAJ}_{\text{C}}^{(1)}$) control charts
$w_2(e_{2i})$	-	Proposed time-varying parameter for $\text{AEWMAF}_{\text{C}}^{(2)}$ ($\text{AEWMAT}_{\text{C}}^{(2)}$ and $\text{AEWMAJ}_{\text{C}}^{(2)}$) control charts
$w_1(e_{3i})$	-	Proposed time-varying parameter for $\text{AEWMAF}_{\text{E}}^{(1)}$

		($\mathrm{AEWMAT}_{\mathrm{E}}^{(1)}$, $\mathrm{AEWMAJ}_{\mathrm{E}}^{(1)}$, and $\mathrm{AEWMAV}_{\mathrm{E}}^{(1)}$) control charts
$w_2(e_{3i})$	-	Proposed time-varying parameter for $\mathrm{AEWMAF}_{\mathrm{E}}^{(2)}$ ($\mathrm{AEWMAT}_{\mathrm{E}}^{(2)}$, $\mathrm{AEWMAJ}_{\mathrm{E}}^{(2)}$, and $\mathrm{AEWMAV}_{\mathrm{E}}^{(2)}$) control charts
y_{pi}	-	PC of X_i
Y_{pi}	-	PC of C_i^1
Z_i	-	Input observations vector of $\mathrm{MCE}^{(1)}$ control chart

LIST OF SYMBOLS

$dF(\delta)/d\delta$	-	Integral for operation of shift
$d(\mu_{(1)X})$	-	Non-centrality parameter
e_i, e_{1i}, e_{2i}, and e_{3i}	-	Error
$F(\delta)$	-	CDF of shifts
i^{th}	-	i^{th} observation
j^{th}	-	j^{th} observation of i^{th} sample of size n
n	-	Sample size
n_i	-	Time-varying i^{th} sample size
p	-	Number of variables
v	-	Degree of freedom
x_{ij}	-	Variable of interest
$\bar{x}_i$	-	Sample mean of i^{th} observation
X_i	-	Random observations vector
$\bar{X}$	-	X-bar control chart
μ_F	-	Mean of F_i transformation
μ_T	-	Mean of T_i transformation
μ_J	-	Mean of J_i transformation
σ_F^2	-	Variance of F_i transformation
σ_T^2	-	Variance of T_i transformation
σ_J^2	-	Variance of J_i transformation
$\Phi^{-1}(.)$	-	Inverse function of $\Phi(.)$
λ	-	Constant of classical EWMA control chart
γ	-	Constant of score functions
$\gamma_{(t)}$	-	Eigenvalues of Σ
$\chi^2_{(.)}$	-	Chi-square distribution
μ_0	-	In-control mean
μ_X	-	In-control mean vector
μ_{CUSUMF_i}	-	Mean of $CUSUMF_i^{\pm}$ statistics by empirical method
μ_{CUSUMT_i}	-	Mean of $CUSUMT_i^{\pm}$ statistics by empirical method

μ_{CUSUMJ_i}	-	Mean of $CUSUMJ_i^{\pm}$ statistics by empirical method
μ_{CUSUMV_i}	-	Mean of $CUSUMV_i^{\pm}$ statistics by empirical method
$\mu_{MCPC^{(1)}}$	-	Mean of $MCPC_i^{(1)}$ statistic by empirical method
μ_S	-	Mean vector of S_i by empirical method
μ_V	-	Mean of V_i transformation by empirical method
σ_0^2	-	In-control variance
Σ	-	Variance-covariance matrix of X_i
$\sigma_{CUSUMF_i}^2$	-	Variance of $CUSUMF_i^{\pm}$ statistics by empirical method
$\sigma_{CUSUMT_i}^2$	-	Variance of $CUSUMT_i^{\pm}$ statistics by empirical method
$\sigma_{CUSUMJ_i}^2$	-	Variance of $CUSUMJ_i^{\pm}$ statistics by empirical method
$\sigma_{CUSUMV_i}^2$	-	Variance of $CUSUMV_i^{\pm}$ statistics by empirical method
σ_F	-	Variance of F_i transformation by empirical method
σ_T	-	Variance of T_i transformation by empirical method
σ_J	-	Variance of J_i transformation by empirical method
$\sigma_{\mathrm{EWMAU}_i}$	-	Standard deviation of EWMAU_i statistic by empirical method
$\sigma_{\mathrm{EWMADU}_i}$	-	Standard deviation of EWMADU_i statistic by empirical method
$\sigma_{\mathrm{EWMAV}_i}$	-	Standard deviation of EWMAV_i statistic by empirical method
$\sigma_{\mathrm{EWMADV}_i}$	-	Standard deviation of EWMADV_i statistic by empirical method
$\sigma_{MCPC^{(1)}}$	-	Standard deviationof $MCPC_i^{(1)}$statistic by empirical method
Σ_S	-	Variance co-variance matrix of S_i
Σ_Z	-	Variance co-variance matrix based on Σ_S and λ
Σ_E	-	Variance co-variance matrix of E_i
$N(\mu_0, \sigma_0^2)$	-	Normal distributed
$N(\mu_X, \Sigma)$	-	Multivariate normal distribution
μ_1	-	Represents an out-of-control value of μ_0
δ	-	Shift occurs in the process location
δ_{max}	-	Maximum shift

δ_{min}	-	Minimum shift
δ^{*}	-	Shift occurs in the process dispersion
σ^2_{EWMA}	-	Variance of $EWMA_i$ statistic
$\emptyset_1()$	-	Huber function
$\emptyset_2()$	-	Bi-square function

CHAPTER 1

INTRODUCTION

1.1 Background of Problems

Product quality, price effectiveness, and public services are the important aspects to attract the clients and customers. Consequently, to contest in the market, companies focus to serve cost-effective and high-quality products. Product quality is a valuable part that improves a company's revenue and repute, and it is determined by the product characteristics (also known as the variable(s) of interest). Therefore, a company is motivated to produce such a product, which meets a specified quality standard. To achieve a product according to the specified quality standard, we generally minimize the source(s) of variations. The sources are categorized as a random cause and special cause of variations. The random cause variations, also known as natural variations, are considered an integral part of a process and cannot be eliminated completely. A process is declared statistically in-control if it operates under random cause variations. In contrast, special cause variations may appear due to several reasons such as improper adjustment of tools, operators' errors, improper adjustment of the machine, and defective raw material. In brief, special cause variations are not assumed natural part of a process and a process governed by these variations is stated as statistically out-of-control. However, an effective action towards eliminating the special cause of variations results into process in-control state. The intensity of the special cause variations occurring in a process parameter (location and/or dispersion) is quantified in terms of a shift.

Statistical process control (SPC) tools consist of control chart, cause and effect diagram, the histogram of stem-and-leaf plot, check sheet, Pareto chart, scatter diagram, and defect concentration diagram are famous to achieve the stability in the output of the process parameters by eliminating or identifying the shift (Montgomery, 2012). Among these tools, quality control charts are most valuable tools to distinguish a shift in the process parameters. The control chart is a graphical display to diagnose a shift in process parameters. The design structure of the classical control chart contains of centre line (CL), upper control limit (UCL), and lower control limit (LCL). As long as, the plotting statistic remains inside UCL and LCL, a process is known as in-control.

In the continuity, classical control charts include of Shewhart-type control charts, proposed by Shewhart (1931); cumulative sum (CUSUM) control chart, recommended by Page (1954); and exponentially weighted moving average (EWMA) control chart, recommended by Roberts (1959). To diagnose a large-size shifts effectively, the Shewhart-type control charts are famous and also recognized as memory-less control charts. These control charts utilize only present sample information, therefore, they performed effective to diagnose larger-size shift, but at the same time, less sensitive for small-to-moderate size shifts (Montgomery, 2012). On the other hand, the classical EWMA and CUSUM control charts are recognized as memory control charts. In these control charts, we integrate both present and past sample information to compute the plotting statistic which makes them more efficient to diagnose small-to-moderate shifts. Since the classical quality control charts introduced, several enhancements and modifications were recommended to improve the diagnose ability of control charts. The detection ability of a control chart can be evaluated by various performance procedures such as average run length (ARL). ARL is the average number of samples in-control until an out-of-control signal is triggered (Sanusi *et al.*, 2018).

1.2 Memory Control Charts

Many researchers, quality engineers, and practitioners introduced modifications and enhancements in the basic structures of classical memory control charts (Page, 1954; Roberts, 1959) by taking into account several circumstances and suitable conditions of a real-life process. For instance, Lucas (1982) designed a combined Shewhart-CUSUM control chart to identify different sizes of shifts. Likewise, for simultaneous monitoring of the process parameters, Chen *et al.* (2001) suggested maximum EWMA (MaxEWMA) control chart. Capizzi & Masarotto (2003) developed adaptive EWMA (AEWMA) control charts using score (Huber and Bi-square) functions and the classical EWMA statistic, denoted as $\mathrm{AEWMA_E}$ control charts. The $\mathrm{AEWMA_E}$ control charts structures consist of time-varying parameters instead of constant parameters. Due to time-varying parameters features, $\mathrm{AEWMA_E}$ control charts are useful to discover different sizes of shifts in the process location. Also, these control charts are helpful to handle the inertia issue. Similarly, Jiang *et al.* (2008) designed an adaptive CUSUM (ACUSUM) scheme using Huber function and classical EWMA statistic, named as $\mathrm{ACUSUM_E}$ control chart. Like $\mathrm{AEWMA_E}$ control charts, the $\mathrm{ACUSUM_E}$ control chart time-varying parameter also helps to diagnose different sizes of shifts. For simultaneous process parameters monitoring, Chen *et al.* (2001) designed a single MaxEWMA scheme. An output statistic of MaxEWMA control chart is the maximum value (magnitude) of the plotting statistics of EWMA for location and dispersion.

The MaxEWMA control chart performed well against the combination of $\bar{X}$ (x-bar) and S schemes to distinguish a shift that occurs either in process location or dispersion. Khoo *et al.* (2010) redesigned the idea of Chen *et al.* (2001) to maximum double EWMA, called as MaxDEWMA control chart. The output statistic of the MaxEWMA control chart is used as input for the conventional EWMA control chart. The MaxDEWMA control chart utilized the maximum value of either conventional EWMA control chart for process location or dispersion. Besides, the MaxDEWMA control chart handles the variable sample size (VSS) problem. Zhang *et al.* (2012) recommended and offered an adaptive control chart. They integrated the statistics of generalized likelihood ratio test and the conventional EWMA scheme. Abbas *et al.* (2013b) designed mixed EWMA-CUSUM, named as MEC control chart for the process location. The MEC scheme methodology uses mixed technique of the classical memory control charts. The output statistic of the conventional EWMA control chart is used as an input statistic for the traditional CUSUM control chart. The MEC control chart is effective to identify small shifts. Later, Abbas *et al.* (2013a) expanded the concept of the MEC control chart from the process location to process dispersion. Later, Zaman *et al.* (2015) contributed a mixed idea of CUSUM-EWMA (MCE) control chart to monitor the process location. It is worthy to mention, the MCE control chart is an inverse version of the MEC control chart which is designed by Abbas *et al.* (2013b). Therefore, the MCE control chart used plotting statistics of the classical

CUSUM control chart as an input for the classical EWMA schemes. The MCE control chart is effective to distinguish small shifts in the process location against to some existing control charts. The traditional CUSUM and EWMA control charts are special cases of MEC and MCE control charts when specific choices of parameters are considered.

The above-mentioned control charts serve the purpose to monitor one or more related characteristics in independent manner. To monitor multi-related characteristics jointly, multivariate control charts were proposed, namely multivariate CUSUM (MCUSUM), Hotelling's T^2, and multivariate EWMA (MEWMA). Hotelling's T^2 control chart proposed by Hotteling (1947) to identify large shifts in the process mean vector. Mainly, Hotelling's T^2 control chart is an extended form of $\bar{X}$ (X-bar Shewhart-type) control chart. In contrary, to diagnose small-to-moderate shifts in the process mean vector, Crosier (1988) and Pignatiello Jr & Runger (1990) suggested MCUSUM control charts. Similarly, Lowry *et al.* (1992) recommended the MEWMA control chart to identify small-to-moderate shifts in the process mean vector of multi-related characteristics. Recently, Ajadi & Riaz (2017) designed multivariate MEC control charts to handle the shift of the process location vector for multi-related characteristics.

Classical and advanced memory control charts are famous and most valuable tools of SPC to handle small-to-moderate shifts in the process location parameter (Nazir *et al.*, 2016). Besides the several advantages of the memory control charts, there are some rooms to improve or extend their methodologies. For example, procedures of $\mathrm{AEWMA_E}$ and MCE schemes do not exist for monitoring dispersion parameter. In other words, the $\mathrm{AEWMA_E}$ and MCE schemes are designed to handle only process location, but they can be designed to monitor a process dispersion, too. Similarly, the MCE scheme is utilized to monitor related characteristics separately instead of jointly. Similarly, MEC control charts efficiently identify a shift either in the process location or in the process location dispersion independently; they could be developed for simultaneous monitoring as well. Further details about their limitations are given in Section 1.3.

1.3 Problem Statement

In light of the background of problems, the problem statement of this study is described as follows:

i. A practitioner has an interest in the stability of both location and dispersion parameters (Abujiya *et al.*, 2016). The AEWMA_E and MCE control charts help to monitor the location parameter of a process. It is valuable to mention that the concept of the AEWMA_E and MCE control charts are not explored to handle the process dispersion shift.

ii. There is no explicit rule to choose an optimal value of reference parameter of classical EWMA control chart to detect a specific shift (Hawkins & Wu, 2014). Therefore, it does not guarantee that either the AEWMA_E control charts detect the particular shifts or not in which practitioners are interested.

iii. The MEC control charts are designed to identify a shift either in a process location or dispersion parameter independently (Abbas *et al.*, 2013a, 2013b). Therefore, the MEC control charts are incapable to diaganose a shift simultaneously in the process parameters.

iv. The MCE control chart is effective to handle a process location shift of multi-related characteristics independently (Zaman *et al.*, 2015), while quality engineers, researchers, and practitioners are often interested to monitor multi-related characteristics jointly. The MCE control chart is effective to monitor a process location shift of multi-related characteristics independently (Zaman *et al.*, 2015), while quality engineers , researchers, and practitioners are often interested to monitor multi-related characteristics jointly.

v. The in-control ARL of multivariate control charts are expected to deviate from the intended level when variables are highly correlated (Montgomery, 2012).

vi. In a multivariate control chart, a shift is distributed among process variables through Mahalanobis distance (MD) statistic. However, as p increases, it becomes hard to find which of variables are the cause of out-of-control (Montgomery, 2012).

vii. The MD statistic is based on the inverse of the variance-covariance matrix. The inverse of the variance-covariance matrix is misinterpreted when the variables of interest are highly correlated (Leys *et al.*, 2018).

1.4 Motivation

Many researchers have contributed to enhancing control chart's performance (see Section 1.2), but these control charts perform effectively when certain ideal conditions are fulfilled. Therefore, the motivation of this work is to recommend control charts by considering the limitations of existing studies as mentioned in Section 1.3. These are based on the following points:

i. To develop an adaptive EWMA control charts using the classical CUSUM statistic, named as $\mathrm{AEWMA_C}$ control charts to monitor a particular shift in the process parameters.
ii. Offering an adaptive CUSUM control charts utilizing the classical CUSUM statistic, named as $\mathrm{ACUSUM_C}$ control charts to monitor a specific shift in the process location parameter.
iii. Constructing $\mathrm{AEWMA_E}$ and MCE control charts to identify a shift in the process dispersion parameter.
iv. Introducing the MEC schemes to handle the shift jointly of the process parameters.
v. Developing MCE control chart to monitor the shift in the process location vector of multiple quality characteristics.
vi. To establish an advanced form of multivariate control charts for small-to-moderate and as highly correlated variables to detect small shift timely.

1.5 Research Questions

Background of problem and problem statement along with the study motivation gave rise to the following research questions.

i. How $\mathrm{AEWMA_C}$ and $\mathrm{ACUSUM_C}$ control charts can diagnose various sizes of shift in the process location?
ii. What significant gain can be accomplished when the $\mathrm{AEWMA_C}$ and $\mathrm{AEWMA_E}$ control charts are constructed to distinguish a shift in the process dispersion?
iii. What significant gain is achievable when the MCE control chart is extended to monitor a process dispersion shift?

iv. How MEC control charts can be developed to monitor a shift in the process parameters jointly to achieve significant performance?
v. How the desired results can be achieved when MCE control chart is designed to monitor multi-related characteristics jointly for the process mean vector?
vi. What are the reliable performance measures for the proposed control charts, and how these possibilities can be carried out for comparison purposes?
vii. How the proposed control charts significantly gain outstanding performance against the existing counterparts for the same motivation?
viii. What the application of proposed control charts is convenient for practitioners to monitor real-life processes?

1.6 Research Objectives

The objective of this research is to design new memory control charts for the adequate and optimal overall performance of the process parameters. Therefore, the following research goals based on problem statement and motivation have been outlined:

i. To construct an adaptive EWMA control charts utilizing the optimal reference parameter of the conventional CUSUM control chart and score (Huber and Bi-square) functions, namely AEWMA_{C} control charts, to identify a certain range of shift in the process parameters.
ii. To design an adaptive CUSUM control charts applying optimal reference parameter of the standard CUSUM control chart and score functions, denoted as ACUSUM_{C} control charts, to diagnose various sizes of shift in the process location.
iii. To develop AEWMA_{E} and MCE schemes for the process dispersion. So, the practitioners, quality engineers, and researchers can benefit from the proposed control charts to keep the stability of process dispersion.
iv. To design the MEC control chart to monitor a shift in the process parameters simultaneously. To reach this objective, the classical memory control charts structures are combined.

v. To propose multivariate MCE control charts to monitor the shift jointly in the process mean vector of multiple quality characteristics. To achieve this target, design structures of MCUSUM, MEWMA, and principal component analysis (PCA) control charts are used (Farokhnia & Niaki, 2019).

1.7 Scope and Limitations of Study

The scope of this study is categorized into three main aspects including theoretical, computational, and practical. Besides, limitations of the proposed study, score functions, and descriptions of real-life data also part of this section.

i. Theoretical aspect

This aspect describes the rationality of mathematical properties of the classical memory control charts. Further, it highlights the designing procedures of the proposed memory control charts based on mixed, adaptive, and simultaneous methods for the stability of the process parameters. Also, mathematical definitions and properties of performance evaluation measures to analyse the proposed control chart's performance are also discussed.

ii. Computational aspect

To show the superiority of all proposed control charts against some other control charts, numerical results needed. Therefore, to carry out the computational procedure, the Monte Carlo simulation technique is utilized to calculate the run length (RL) properties for all proposed control charts. The algorithms for all proposed control charts are developed in MATLAB. Besides, graphical techniques such as line plot, scatter plot, and dot plot are also used to compare control charts performances.

iii. Practical aspect

Besides the numerical and graphical comparison of the proposed control charts against some of the existing counterparts, the proposed control charts are also implemented on real-life data to illustrate procedural details to quality engineers, researchers, and practitioners. This research considered real-life data sets from manufacturing, banking sector, and meteorological industries.

iv. Limitations

This study also has some limitations which are associated with the proposed control charts constraints, parameters, sample size, designed structures, behavior of interested characteristics, and sampling methods. So, any deviances in these strongly influence the findings, analysis, and interpretations. For example, constraints and parameter values rather than that will increase or decrease the out-of-control ARL. Besides, sample techniques such as simple random sampling (SRS) plays a vital role to enhance their performance of the study instead of others. Similarly, the proposed study provides efficient results if characteristics of interest follow a normal distribution. Correspondingly, the designed structures of the proposed study only served the listed objectives in the light of background of problems and problem statement.

v. Score functions

The score functions such as Huber and Bi-square functions (Capizzi & Masarotto, 2003) are famous among the quality engineers, practitioners, and researchers because of their ability to detect different sizes of a shift in the process parameters effectively as compare to others. The Huber and Bi-square functions enable the parameters of memory control charts as as a time-varying via self-adjustment to react according to the nature of a process parameter shifts.

vi. Real-life data

The proposed univariate and multivariate control charts are implemented with real-life data sets to show practical aspects. For example, the real-life data from banking sector such as cost of processing mortgage loan application fee and thickness of a metal layer on silicon wafers, diameter of cylinder bores, real-life data of wafers, parts manufactured by an injection molding process, and inside diameter of cylinder bores in an engine block from manufacturing are considered for proposed univariate control charts. Similarly, average wind speed data for every ten minutes generated at 10m (meters), 20m, 30m, and 40m above the ground levels is used for multivariate proposed control charts.

1.8 Significance of Research

The occurrence of new quality issues and concerns in the different industrial setups such as manufacturing is a continuous process. However, the implementation of the traditional control charts may not resolve all the issues perfectly. Therefore, quality engineers, researchers, and practitioners continue to search for more enhanced control charts that provide stability for the process parameters. Hence, the goal of this research is to propose advanced memory control charts that can be beneficial to improve the process efficiency against existing control charts.

1.9 Structure of the Thesis

This thesis includes seven chapters. A short introduction of every chapter is reviewed as follows:

Chapter 1 describes the general introduction of SPC control charts. The background of problems, problem statement, motivation, research questions, and research goals are explained in this chapter. It also presents the scope of the study, the significance of the research, and structure of the thesis.

Chapter 2 offers a broad and thoroughly review of the literature on related topics and concepts. Previous review work on modified and enhanced memory control charts for the process parameters are also discussed. This chapter also explains review work on multivariate control charts, the role of mixed, adaptive, and simultaneously methods in control charts to monitor the process parameters.

Chapter 3 is focused on the research methodology. It introduces the classical memory-less and memory control charts for the process parameters monitoring. It also includes multivariate control charts for the process mean vector. Performance evaluation measures such as extra quadratic loss (EQL), performance comparison index (PCI), average run length (ARL), standard deviation of run-length (SDRL), and relative average run length (RARL) measures are also part of this chapter. Lastly, score functions such as Huber and Bi-square methodologies are also described.

Chapter 4 is about the proposed memory control charts research methodologies. It explains the structures of the suggested $\mathrm{AEWMA_C}$ and $\mathrm{ACUSUM_C}$ control charts to handle the process location shift. Likewise, it also defines the proposed $\mathrm{AEWMA_C}$ and $\mathrm{AEWMA_E}$ control charts to handle a shift in the process dispersion. Furthermore, it provides the research methodologies of the proposed MEC control charts for simultaneous monitoring of the process parameters. The MCE control charts to handle the shifts in the process dispersion of a single variable, and to handle the shifts of the process mean vector are also part of it. Finally, some existing control charts for some specific values of parameters/constants became special cases of the proposed control charts also part of this chapter.

Based on results, Chapters 5 deals with performance evaluation of the proposed control charts versus other control charts. It contains the comparative analysis of control charts to diagnose shifts in the process parameters. Numerical results and graphical presentations are used to measure the effectiveness of control charts. The efficiency of the control charts is judged based on a single shift and a certain range of shifts as well.

Chapter 6 describes the real-life data sets. It also contains the applications of the proposed and other control charts using industrial data for comparison purposes. Finally, Chapter 7 concludes the study with research findings followed by summarizing thesis contributions and recommendations for future research.

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LIST OF PUBLICATIONS

Journal Publications (ISI):

1. Zaman, B., Abbas, N., Riaz, M., & Lee, M. H. (2016). Mixed CUSUM-EWMA chart for monitoring process dispersion. *The International Journal of Advanced Manufacturing Technology*, *86*(9-12), 3025-3039. ISSN: 0268-3768. 2015 JCR Impact Factor: 1.568. Quartile: Q2

2. Zaman, B., Riaz, M., & Lee, M. H. (2017). On the performance of control charts for simultaneous monitoring of location and dispersion parameters. *Quality and Reliability Engineering International*, *33*(1), 37-56. ISSN: 0748-8017. 2015 JCR Impact Factor: 1.457. Quartile: Q2

3. Zaman, B., Lee, M. H., Riaz, M., & Abujiya, M. A. R. (2017). An adaptive EWMA scheme-based CUSUM accumulation error for efficient monitoring of process location. *Quality and Reliability Engineering International*, *33*(8), 2463-2482. ISSN: 0748-8017. 2016 JCR Impact Factor: 1.457. Quartile: Q2.

4. Zaman, B., Lee, M. H., Riaz, M., & Abujiya, M. R. (2019). An adaptive approach to EWMA dispersion chart using Huber and Tukey functions. *Quality and Reliability Engineering International*, *35*(6), 1542-1581. ISSN: 0748-8017. 2018 JCR Impact Factor: 1.457. Quartile: Q3.

5. Zaman, B., Lee, M. H., Riaz, M., & Abujiya, M. R. (2019). An adaptive EWMA chart with CUSUM accumulates error-based shift estimator for efficient process dispersion monitoring. *Computers & Industrial Engineering*, *135*, 236-253. ISSN: 0360-8352. 2018 JCR Impact Factor: 3.518. Quartile: Q1.

6. Zaman, B., Lee, M. H., Riaz, M., & Abujiya, M. R. (2020). An improved process monitoring by mixed multivariate memory control charts: An application in wind turbine field. *Computers & Industrial Engineering*, *142*, 106343. ISSN: 0360-8352. 2020 JCR Impact Factor: 4.135. Quartile: Q1.

7. Zaman, B., Lee, M. H., Riaz, M., & Abujiya, M. R. (2020). An adaptive CUSUM control charts for monitoring process location: An application in silicon wafer field (submitted).