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## Examining the Monitoring of Health Surveillance During a Pandemic: A Review of Methodology

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## RESEARCH ARTICLE

# Examining the Monitoring of Health Surveillance During a Pandemic: A Review of Methodology

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### Abstract

The goal is to examine a common problem is biological analytics and surveillance in health care. These methods can improve greatly the process of monitoring health data to assess changes in the likelihood of Pandemics and disease incidence in a world where medical knowledge is still largely in an embryonic period. Based on an illustration, we suggest that multivariate exponential moving-average (*MEWMA*) control charts are suitable in many cases where detection and inspection of several or more variables over a lengthy period of testing provide for the best analysis of data leading to pre-diagnostic and diagnostic therapy. Though these methods came from the control of quality and continuous improvement in lean manufacturing and service operations, these methods are useful if not a vital application in the analysis of health care and therapeutic data. The indications from this study corroborate earlier findings by others that MEWMA methods fit the diagnostic activity under study. Unfortunately Pandemic Analysis is using oversimplified techniques such as a seven period moving average in analyzing data secure by diagnostic tests which can easily be improved especially in the use modern day analytics based on quality control methods used in other disciplines.

Keywords: Analytical Monitoring, Quality Control applications, Use of Control Charts

## 1 | INTRODUCTION

## 2 | BIOLOGICAL SURVEILLANCE WITH MULTIVARIATE METHODS

Modern bio surveillance involves the monitoring large number and wide range of data from samples of diagnostic and pre-diagnostic data for the purpose of giving health care professional to recognize , detect,

investigate and respond to the outbreaks of disease and pandemics. A central tool in this monitoring in classical disease surveillance migrated to biological surveillance is the use of multivariate quality control methods. Fricker (2007) applied multivariate statistical control methods with an application of multivariate quality control (MQC) to syndromic surveillance. Fricker et al. (2008) continued the earlier study by focusing on directionally sensitive procedure in

bio surveillance. Joner et al. (2008) produced a one sided multivariate exponentially weighted moving-average (MEWMA) control chart for the analysis of health data. Niaki and Ershadi (2012) used a solution to solve a statistically constrained economic model of a MEWMA control chart in which external intangible costs were considered. Shen and Cooper (2012) produced an MPC Decision Analytical model for bio surveillance. Last, Yahav and Schmueli (2013) introduced in practice directionally sensitive MPC charts to bio surveillance methods. They examined four such techniques and came to conclusions based on simulated data, but suggested further research in the application of these methods. Last, Jarrett (2016) indicated the need and motivation for implementing data analytical methods in the health care environment.

### 3 | MEWMA MODELING AND QUALITY CONTROL

Previously Ord, Koehler, Snyder and Hyndman 2009; hereafter, (OKSH) recognized the usefulness of monitoring social or economic processes is a clear application of the notion of statistical process control (SPC). They extended the notions of control by Shewhart Control Charting to that of monitoring univariate time series. Furthermore, OKSH suggested the use of EWMA charts for residuals, which will be effective in detecting level shifts and suggest their use in detecting shifts in variability. This improved process could also be explored by expanding the analysis to the multivariate case. OKSH suggested that we examine the ideas explored by Lowry, Woodall, Champ and Rigdon (1992, hereafter LWCR), Pan and Jarrett (2004) and Rungar, Barton, Del Castillo and Woodall (2007). The multivariate form of the EWMA control chart simultaneously monitors two or more related processes in an exponentially weighted moving-average control

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chart. For example, if one applies a MEWMA chart to monitor temperature and pressure in a plastic injection molding process. Each MEWMA point incorporates information from all the previous subgroups or observations in combination with a user defined weighting factor. MEWMA charts can help you detect small process shifts quicker than other multivariate charts, such as the  $T^2$  control chart. Another advantage of MEWMA charts is that they are not greatly influenced when a small or large value enters the calculation. Also, MEWMA charts can be custom tailored to detect any size shift in the process. Because of this, they are often used to monitor in-control processes for detecting small shifts away from the target.

Multivariate process control simultaneously monitors several processes in combination. Previous work on multivariate monitoring since LWCR include a large number of papers in the quality monitoring literature [i.e., Lowry and Montgomery, 1995; Sullivan and Woodall, 1996; Djauhari, 2005; Khoo and Quah, 2003; Kruegel, Valuer and Vigna, 2005; Ye and Chen, 2001; Ye, Chen and Borrer, 2004; Ye, Giardano and Feldman, 2001; Ye, Vilbert and Chen, 2003; Bersimis, Psakaris and Panaretos, 2006; Khoo, 2003, Yeh, Wang and Wu, 2004; Pan and Jarrett, 2004; Yang and Rahim, 2005, Jarrett and Pan, (2007a, 2007b, 2014) , and finally Pan and Jarrett, 2014]. These monitoring methods employ the Hotelling  $T^2$  statistic for a current samples.

Exponentially weighted moving average (EWMA) charts which are more sensitive to moderate shifts in parameters than Univariate charts are widely used in univariate cases (Crowder, 1989; Lucas and Saccucci, 1990). LWCR extended the Univariate EWMA control chart to the multivariate case by simulation. They noted that the multivariate EWMA (hereafter MEWMA) chart has greater sensitivity to shifts in the mean than more traditional Hotelling  $T^2$  control methods.

An alternative MEWMA scheme is Pan (2005), which builds the Hotelling  $T^2$  of the variables before the formation of the EWMA of the  $T^2$ s. Lui (1996) presented an improvement for MEWMA. Runger and Prah (1996) used Markov chain analysis to calculate the ARL for MEWMA and Prah and Runger

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(1997) discussed the design of the same scheme. However, all these studies assumed the processes to be serially independent. Others chose to study the usefulness of MEWMA methods as well. Stoumbus and Sullivan (2002) investigated the effects of non-normality on the performance of the MEWMA control chart, and its special case, the Hotelling's Chi-Square control chart when applied to individual observations. The purpose in this case was to monitor the mean vector of a multivariate process variable. Khoo studied the sensitivity of MEWMA control charts under other circumstances. In addition, Lee and Khoo (2006) explored a method for optimally designing multivariate EWMA charts based on the measures of average run length (ARL) and median run length (MRL). In this study, we utilize the concept of sensitivity ratios based on the works of Hanson, Eskridge, Steadman and Madisa (2009) and Väisänen and Hyttinen (2007) who argued that sensitivity ratios are a superior method to assess quality in the areas of bioelectric measurements, plant disease screening methods and others involving new technology. The sensitivity ratio is a statistic specifically developed for comparing for different measuring methods and is not based on any particular assumption about how the measuring methods or scales are related. Hence, our purpose is to share new research in the evolution of monitoring processes by comparing results of experiments.

The Pan MEWMA scheme builds the Hotelling  $T^2$  of the variables before order of construction steps is the statistic of MEWMA chart. Pan (2005) used integral equation method to compute the ARL's of MEWMA charts for in-control and out-of-control situations without the presence of serial correlation. All MEWMA method variations are multivariate EWMA schemes.

The above schemes have a common problem, that is, they cannot be directly employed when the processes are serially correlated. An indirect way to apply the MEWMA schemes for serially correlated processes is to adopt Alwan and Roberts' (1988) approach. They suggest estimating the residuals, i.e., one-step-ahead forecasting errors, of the Autocorrelated process. In turn, they apply traditional control charts for the residuals. Extending this approach to multivariate cases, one can apply the above MEWMA scheme to

the residuals of the serially correlated multivariate processes, until the processes are modeled properly and the initial number of observations is sufficiently large and the residuals are asymptotically independent over time. At this point, we determine the sensitivity of these approaches to changes in process parameters in the presence of serial correlation. Since the process parameters are usually unknown, the appropriate estimation and use of the covariance matrix is vital for correct execution of MEWMA. This may occur if the direct sample variance is a biased estimate of the population variance for a serially correlated process.

The main reason for utilizing multivariate quality control charts occurs in the situation where the collected data for two or more variables show cross-correlation. In this event a multivariate control chart should utilize a better result than studying independent control charts for each variable and is currently available in quality control software. We will in the next section, consider applications of MEWMA charts to monitor bio surveillance data to understand the meaning and application of these charts in a simulated experiment. The data for the analysis came from a hospital source collected over a sufficiently long time to produce enough data for analysis by the methods used in this study. Patient information is not available but the sample size produces enough and data for MEWMA analysis and the results are such that the methods used produced valuable results and interpreted through a series of multivariate control charts easily produced by standard quality control and improvement software. The user needs only to learn the meaning the control charts illustrated in the next sections.

### 4 | AN ILLUSTRATION OF THE MEWMA CONTROL CHART

We consider a bio surveillance procedure where data is collected on five variables (A, B, C, D and E). Based on the results of Table 1 where we exhibit the correlation coefficients and their "**p-values**" for the crosscorrelations of the five variables denoted before. Five of the correlation coefficients are large enough to have produces p-values which are small



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Note, that although ARL is often the usual measure for multivariate chart performance, it is not the only criterion, and may have shortcomings. There is much to learn from using MEWMA in bio surveillance especially in the light of health and medical diagnostic processes which may have much great numbers of variables to consider when applications are merited. Alternatively, studies using other criteria such AD (average delay) or MRL (median run length) may prove superior in establishing the MQC decision point. In the future, Rare Event control charts may improve analysis and diagnosis which are now standard on quality control and improvement software. Last, standard office software such as Excel do not include these methods, hence, specialized software programs such as demonstrated in this study will be employed in practice.

To summarize, the elementary use of diagnostic analysis will not easily prevent and cure Covid-19. In particular, the use of a seven period moving average a simple but very restrictive statistic in its use and interpretation. Thorough use of sophisticated analyses utilizing often quality control and continuous improvement will enable a better future for controlling the environment of the Coronavirus era that we are living under. The examples utilized in this document suggest better use of medical strategies to solve the problems of the current Pandemic. The response by the current administration in preparing the nation for the Pandemic is unremarkable.

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