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PRIORITIZED EWMA CONTROL CHART FOR TIME SENSITIVE PROCESS

ALI FADHIL ABDULJABBAR

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By

ALI FADHIL ABDULJABBAR

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By

ALI FADHIL ABDULJABBAR

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Chairman : Anwar Fitrianto, PhD
Institute : Mathematical Research

Numerous challenges are faced by manufacturing industries in recent years, and process variation becomes the major source of poor quality in manufacturing control. A control chart in statistical process control (SPC) is a powerful tool to achieve stability and improvement in process capability by reducing the variability. A manufacturer normally has to deal with time-series observations for monitoring the processes. New studies recommend using machine learning techniques due to the ability of these methods to automatically detect data patterns and to exploit such data patterns for future prediction and process improvement that usually evaluated through control charts.

This research outlines the exponentially weighted moving average(EWMA)control charts that are applied on time series data of a dairy distribution process. Different data are simulated from the AR, MA, and ARMA processes. MATLAB -based simulations of EWMA control charts for AR(1), AR(2), MA(1), MA(2), ARMA(1,1), and ARMA(2,2) are performed for each process at various sample size and replication, The average run length (ARL) is a significant measure to assess the performance of the control chart. In this work, an ARL-based EWMA chart is discussed for monitoring the process variance for AR, MA, and ARMA processes. The efficiency of these charts is compared in terms of ARLs. The EWMA for ARMA(2,2) chart is more efficient than other discussed charts in terms of ARLs. A real example is given illustrating the proposed chart in the industry.

The work shows that the EWMA control chart highlights several data points exceeding the upper control limit for AR(1), MA(1), and ARMA(1,1) processes, which indicates that the process is out of control at these points, while shows that the process is in control for AR(2), MA(2), and ARMA(2,2). Such analysis ensures a

stable quality and shows that each production process requires to be maintained within a predefined time limit. Moreover, certain industries need such a capable system to detect the quality at an early stage before it over shifted. The results of applying the AR, MA, and ARMAshow that the developed model can succeed to approximate time series data patterns, and as the order of these models has increased the ability to fit observations become more accurate for the cases studied in the control chart.

The significant insight of the presented model in this work is to focus on the benefits of using EWMA on different types of time series data. This action will enhance the quality of the products, by offering an effective solution that will lower the time consumed during the management of the transportation time of the product's processes.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

CARTA KAWALAN EWMA DIPRIORITIKAN BAGI MASA–PROSES SENSITIF

Oleh

ALI FADHIL ABDULJABBAR

September 2020

Pengerusi : Anwar Fitrianto, PhD
Institut : Penyelidikan Matematik

Pelbagai cabaran telah dihadapi oleh industri pembuatan sejak tahun kebelakangan ini, dan variasi proses menjadi sumber utama penurunan kualiti dalam kawalan pembuatan. Carta kawalan dalam kawalan proses statistikal (SPC) merupakan alat yang sangat berkuasa bagi mencapai stabiliti dan peningkatan dalam keupayaan proses melalui pengurangan variabiliti. Seseorang pengilang biasanya terpaksa berurusan dengan cerapan siri masa bagi pemantauan sesuatu proses. Kajian baharu mengesyorkan supaya menggunakan teknik pembelajaran mesin disebabkan kebolehan kaedah tersebut yang secara automatik dapat mengesan pola data dan mengeksploitasi pola data tersebut bagi peramalan masa hadapan dan peningkatan proses yang biasanya dinilai melalui carta kawalan.

Penyelidikan ini menggariskan carta kawalan purata bergerak berwajaran eksponen(EWMA) yang diaplikasikan ke atasdata siri masa bagi taburan proses tenusu . Data yang berbeza telah disimulasikan daripada proses AR, MA, dan ARMA. Simulasi berasaskan MATLAB bagi carta kawalan EWMA untukAR(1), AR(2), MA(1), MA(2), ARMA(1,1),dan ARMA(2,2) telah dijalankan bagi setiap proses pada pelbagai saiz sampel dan replikasi, purata panjang jalan (ARL) merupakan ukuran yang signifikan bagi menilai prestasi carta kawalan. Dalam kajian ini, carta EWMA berasaskan ARL telah dibincangkan bagi pemantauan proses varians bagi proses AR, MA, dan ARMA. Kcekapan carta tersebut telah dibandingkan dari segi ARL. EWMA bagi carta ARMA(2,2) adalah lebih efisien daripada carta lain yang telah dibincangkan dari segi ARL. Contoh sebenar telah diutarakan bagi pengilustrasian carta yang disyorkan dalam industri tersebut.

Kajian ini menunjukkan bahawa carta kawalan EWMA mengetengahkan beberapa titik data yang melebihi had kawalan atas bagiproses AR(1), MA(1), dan ARMA(1,1), yang memperlihatkan bahawa proses tersebut adalah di luar kawalan bagi data tersebut, di samping menunjukkan bahawa proses tersebut adalah dalam kawalan bagi AR(2), MA(2), dan ARMA(2,2). Analisis tersebut memastikan kualiti yang stabil dan menunjukkan bahawa setiap langkah distribusi produk memerlukan sekiranya diulangi dengan mengekalkannya dalam had masa yang pratertakrif. Tambahan lagi, industri tertentu memerlukan suatu sistem yang berkemampuan untuk mengesan kualiti pada peringkat awal sebelum ianya teranjak. Dapatan pengaplikasian AR, MA, dan ARMA menunjukkan bahawa jaringan model yang dibangunkan telah berjaya dalam pengesanan pola data runut masa bagi kes yang dikaji dalam carta kawalan.

Impak yang signifikan bagi model yang diutarakan dalam kajian ini ialah kesannya ke atas prestasi carta kawalan, yang kelihatan seperti pengurangan yang jelas dalam julat antara had atas dan bawah. Tindakan tersebut akan meningkatkan kualiti produk, sebagai kajian kes, dengan menawarkan suatu penyelesaian yang efektif yang akan mengurangkan masa yang diambil ketika pengurusan masa pengangkutan suatu proses produk .

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This thesis was submitted to the Senate of the Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science. The members of the Supervisory Committee were as follows:

Anwar Fitrianto, PhD
Senior Lecturer
Faculty of Science
Universiti Putra Malaysia
(Chairman)

Jayanthi a/p Arasan, PhD
Associate Professor
Faculty of Science
Universiti Putra Malaysia
(Member)

ZALILAH MOHD SHARIFF, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

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LIST OF ABBREVIATIONS

SPC	Statistical Process Control
EWMA	Exponentially Weighted Moving Average
ANN	Artificial Neural Network
AR	Autoregressive
MA	Controlled chart for the mean that employs the current mean average and a handful of earlier means to create every new moving average
ARMA	Autoregressive Moving Average
CNN	Customized Neural Network
SQC	Statistical Quality Control
QC	Quality Control
SQS	Statistical Quality Scale
CUSUM	The Cumulative Sum
CL	Confidence Limits
UCL	Upper Control Limits
LCL	Lower Control Limits
AEWMA	Adaptive EWMA
AR(1)	First-Order Autoregressive
AR(2)	Second-Order Autoregressive
L	Constant
wij	Weight terms
αpi	Activation for each node
δpi	Error Term
E	Error function
k	Subscript indicates a summation over all nodes in the downstream layer

j	Subscript indicates the weight position in each node
ε	The learning rate and determines the size of the weight adjustments during each training iteration
ASPC	Algorithmic Statistical Process Control
IC	In-Control
ARL	Average Run Length
ARL_0	In-Control ARL
ARL_1	Out-Of-Control
EWMAST	The Single Adaptive EWMA

CHAPTER 1

INTRODUCTION

1.1 Background

Control charts are still one of the main important tools of statistical process control for determining whether a process is performing as projected or if there are some abnormal reasons for variations. A process is out of control if a point falls outside the control limits or a series of points exhibit an abnormal pattern. To control the quality of a time series process, statistical process control (SPC) is used as a method that employs statistical techniques for monitoring and controlling a process. SPC is usually used to improve the quality of products. The control chart plays the most important role in SPC. Control charts help to monitor the behaviour of the process to determine whether it is stable or not. Statistics are applied to control manufacturing processes. Statistical process control (SPC) is a specific approach to monitor the operational process in order to identify special variations. Specific variations are out-layers, which exceed the common variation.

Monitoring productivity and improving the quality of industrial service operations and processes are the most commonly used functions amongst the techniques of SPC for statistics. SPC involves the deployment of control charts. These are graphical tools that are used to monitor the production process and determine the specific reasons for variations in the outcome of the main conflict in the performance of the process stemming from the ubiquitous main causes of variance that are involved in the process. Such a method of statistical control of quality technology is popular worldwide and is employed frequently in determining the changes in the process to avoid the manufacturing of faulty products. When considering the different forms like process mean shifts, the main emphasis is given to the changes in the process for a majority of the designs as well as quality in the control chart. Particularly, the Shewhart-type chart is employed for detecting these shifts as mentioned in (De Vries and Reneau, 2010; Nelson, 1984; Westgard et al., 1981).

According to (Montgomery, 2007), certain characteristics of quality define the quality most of the time, which are mostly correlated. For quality, all these characteristics need to meet a few conditions. The product quality depends on the mutual impact that includes most of the input variables rather than just their individual values. In the SPC, most of the approaches are designed for control charting of small quantity variables that also include the final product's quality and evaluating each of these individually. However, in the business process, for most applications, this does not seem to apply. It overlooks the gathered data on the process variables. It is almost impossible for the researcher to evaluate more than 2 or 3 charts to maintain the product and process qualities. In real-time practice, only some procedures are found to encourage a process at a given time and are very useful. As demonstrated by (Lark et al., 1999), different arrangements for such dimensions is just a replica image of the same underlying procedures.

The supply chain is of particular importance to the milk market. Milk is a food product that needs to be stored properly. In general, milk may be collected in two ways: either collected directly from a farm or delivered to a collection centre, with the first way being particularly preferred by large farms(Fałkowski et al., 2013). In dairy farms, milk is stored in low-temperature milk tanks to help prevent the development of microorganisms. Most frequently, milk is collected every second day from agricultural farms in tank trucks specially dedicated to this purpose. Then, milk is transported to processing plants where it is processed. The second way of milk collection was important in times of the centrally planned economy. This was the only way for a farmer to deliver milk to a collection centre operated by a dairy enterprise (Fakowski, 2012).Production logistics involves the flow of information and materials within the entire production process. According to (Prajogo et al., 2016), the tasks of production logistics include organization ,control and planning of the flow of raw materials, parts of cooperative elements, and the materials needed by an enterprise. Production logistics is aimed at reducing production costs. Distribution logistics aims to coordinate processes at each stage of distribution related to the supply of a final product to a consumer via distribution channels. The longer the distribution channels, the longer the duration of delivery of a final product, and the greater the losses of products.

Moreover, longer distribution channels result in greater differences in the prices paid by a consumer and received by an agricultural producer. Distribution logistics involves the delivery of the right product within the right time limits to the right customer. In this process, both the customer service process and the flow of information in both directions are important .Not only do the changes in the organization of supply chains increase requirements but also create opportunities for gaining access to new markets and vertically organized supply chain systems. Also, the liberalization of Polish trade and the privatization of milk processing enterprises have opened the Polish dairy sector to greater foreign competition. These actions have contributed to an increase in investment in the Polish dairy sector (Dries et al., 2009). A study of changes in milk supply chains was conducted by (Rabinowitz and Liu, 2014). Its results show that the processing and retail trade creates a need for investments in agricultural farms, and affect the retail price of milk. An analysis of prices of products of agricultural origin within the food chain is a complex issue as agricultural raw materials are, as a rule, processed and differentiated through the process of adjustment to the consumers requirements (Almås and Brobakk, 2012). The milk product supply chain refers to the complete chain of values, retail sales, with the consumer as the final link. The milk supply chain comprises primary food production, feed component production, cattle feed production, livestock production and milk production, milk processing, wholesale and retail sales, and consumption (Jarzębowski, 2013).

This study develops a non-linear quality model for enhancing quality by reducing the time-sensitive process.Then,the developed model is applied to the present Exponentially Weighted Moving average (EWMA) control chart for the time-sensitive process. Furthermore, the study develops a prioritized EWMA control chart for the process that is capable of non-linear minimization because of sensitivity in time delay. Moreover, this study offers different insights and strategies that can be implemented to improve the nonlinear scheme further in terms of the exponentially weighted moving average chart having specific references to time-sensitive data. This research will also help reveal the significance of controlling or maintaining the quality of production processes by employing the EWMA.

1.2 Problem Statement

An alternative to the standard Shewhart control charts that are often exploited to monitor time-series observations is the exponentially weighted moving average (EWMA) chart. The main advantage of the EWMA chart is its capability to sense the shift in the process means better than a Shewhart chart. Several approaches have been used to make these choices, but there is a lack in the action or the decision making after evaluating the control chart and the analysis of the AR, MA, and ARMA process in terms of alternative evaluation.

A case study with time-series observations like all other agribusinesses, the dairy supply chain is a time-based complex chain . Technically, the dairy chain begins with the production of raw Dairy and ends when institutions, other processors, and consumers use the products produced by the value chain. The chain of Dairy production has three major adjustable times; the production and pre-processing times, transportation times, and distribution times. A diagram can be used to express the chain and is demonstrated in Figure 1.1.The following equation can be used to express the empirical system formula for the Dairy quality:

$$\mathrm{Mq} = \mathrm{p}_1\mathrm{C} + \mathrm{p}_2\mathrm{V1} + \mathrm{p}_3\mathrm{V2} + \mathrm{Procs} \tag{1.1}$$

where Mq represents the Dairy quality function,p_1, p_2, p_3 represent the three-time parameters' coefficients V1 (transportation), C (production and pre-processing), and V2 (distribution times) respectively.

Figure 1.1 : Dairy production Chain

1.3 Research Questions

This research study was intended to answer or get an explanation of the following questions:

1. How to evaluate the performance of the EWMA control chart for time series data from AR, MA, and ARMA processes via simulation?
2. Are the AR, MA, ARMA are the best to formulate/simulate the product observations, or there is an alternative?
3. Can we use one of the artificial intelligence approaches to modify the quality control chart as an action when evaluating EWMA?

1.4 Objectives

This work examines the practical issues faced while employing the statistical quality control for EWMA control charts and proposes a solution that acts as an action to improve a dairy production chain's measurement as a case study. Therefore, the main objectives of this work are:

1. To analyse the performance of the prioritized EWMA control chart of time-series data for each of AR, MA, and ARMA processes via a simulation study.
2. To analyse and evaluate the performance of the proposed EWMA control chart for each of AR, MA, and ARMA processes based on the average run length (ARL).
3. To simulate the above models on real dairy observations with EWMA performance of the quality control chart.

1.5 The significance of the Study

This study is intended to investigate the concept of prioritized EWMA control charts by considering the time-sensitive process. The traditional control charts like X-bar and R-charts may be inadequate sometimes when the process exhibits abnormal situations which could lead to wrong decisions. When we are interested in detecting small shifts, the EWMA control chart provides the correct picture to make the right decisions without affecting the process unnecessarily. In the current technological time frame, machines and their maintenance costs are very expensive. Therefore, making use of the enhanced methods to evaluate variations of statistics in the parameters of the chain process of products is of prime importance. This research addresses a time series control chart to express the quality control pattern of the dairy as a case study. The first part of the work discusses the methodology of a time series control chart for analytical data and proposes a fitting model equation for the quality pattern. A comparison of the created network's output with that of the recorded data is done to check the performance of the created network. Moreover, this study will offer different strategies and meaningful insights to be implemented to further enhance the nonlinear scheme with regard to time-sensitive data. This study will also help in understanding the role and importance of controlling or maintaining the quality in the production line.

1.6 Organization of the thesis

This dissertation shows how an EWMA control chart can help system designers and programmers to understand the performance characteristics of time-series data for each of AR, MA, and ARMA processes via a simulation study. The organization of this thesis is as follows.

Chapter 1 provides a background for the thesis insight, problem statements, problem limitations, research questions, and the research objectives. The research significance and outline of the work are also introduced in this chapter .

Chapter 2 introduces the literature review about statistical quality control (SQC) and quality control (QC) as useful tools to test the performance of product quality in detail. We first describe three types of control charts: CUSUM chart, Shewhart chart, and the EWMA chart that our model is built on, as well as provide a breakdown view on how to evaluate the performance of the proposed EWMA control chart for each of AR, MA, and ARMA processes based on the average run length (ARL). The last section in Chapter 2 is focusing on reviewing other related models, and show how our work is distinguished from other works.

Chapter 3 provides derivations of mathematical equations and formulae for the EWMA control charts for time series data of AR, MA, and ARMA processes when process parameters are estimated. This chapter also provides a brief description of the EWMA control chart for time series data of AR, MA, and ARMA processes, which is used as our tool to validate the thesis statement. Then we define time-series observations and the EWMA chart of the AR(1) model to perform a systematic analysis on its performance. Through our modelling framework, we easily spot out the strength and weaknesses of these systems.

Chapter 4 provides an evaluation for the performances of EWMA control charts for time series data of AR, MA, and ARMA processes with estimated process parameters using ARL performances of control charts. This evaluation ensures that the proposed estimated process parameters based charts have similar in-control performances to their known process parameters counterparts. To facilitate the implementation of EWMA control charts for time series data of AR, MA, and ARMA processes, illustrative examples are given.

Chapter 5 details a case study of the implementation and optimal design procedure for the proposed EWMA control charts on real data obtains from a real dairy product.

Chapter 6 concludes the thesis. It summarizes the main contributions of this thesis. Suggestions for further research involving related topics are identified in this chapter.

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APPENDICES

APPENDIX A

1- To model the AR(1), the following commands is used in MATLAB:
model = arima('Constant',0.4,'AR',{0.7},'Variance',.1);

2- The command "rng('default')" is used to put the settings of the default settings are the Mersenne-Twister with seed=0. while the command lines are:
rng('default')
Y = simulate(model,50);

3- Generating many samples (1000) of data set each with 50 observations, use the following commands:

```
rng('default')
Y = simulate(model,50,'NumPaths',1000);
figure
subplot(2,1,1)
plot(Y,'Color',[.85,.85,.85])
title('Simulated AR(2) Process')
hold on
h=plot(mean(Y,2),'k','LineWidth',2);
legend(h,'Simulation Mean','Location','NorthWest')
hold off
subplot(2,1,2)
plot(var(Y,0,2),'r','LineWidth',2)
title('Process Variance')
hold on
plot(1:50,.83*ones(50,1),'k--','LineWidth',1.5)
legend('Simulation','Theoretical',...
'Location','SouthEast')
hold off
```

4- This for using 1000 samples:

```
Y = simulate(model,150,'NumPaths',1000);
Y = Y(101:end,:);
```

5- MA(1) with the following command:

```
model = arima('Constant',0.4,'MA',{0.7},...
'MALags',[1],'Variance',0.1);
```

BIODATA OF STUDENT

Mr. Ali Fadhil Abduljabbar is currently a MS candidate at the Institute For Mathematical Research, Universiti Putra Malaysia. He, obtained his Bachelor, Statistics from the University of Wassit, Iraq in 2008. Prior to his enrollment as a MS candidate, he worked for three years as a teaching staff. His research interests focus on Statistics