REFINED BLEACHED DEODORIZED PALM OIL QUALITY PREDICTION USING MULTIVARIATE STATISTICAL PROCESS CONTROL TOOLS

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ABSTRACT

Multivariate statistical process control (MSPC) has been widely used for quality prediction and monitoring in palm oil refinery processes. Currently, the refined, bleached deodorized palm oil (RBDPO) quality is determined based on the relationship between crude palm oil quality and process parameters, with the assumption that the process is static and not affected by the time-varying characteristic of the palm oil refinery process. However, the prediction is less accurate since the generated regression coefficients from static prediction models do not reflect the current process status and remain constant over time. Therefore, this study was conducted to introduce a new framework for regression coefficients improvement via dynamic prediction models. The dynamic prediction models were developed by integrating the MSPC prediction tool with time-series expansion methods where the prediction models were adapted to new process dynamics. Data collected from an industrial palm oil refining plant were used as the case study in this research. Four MSPC models, namely linear principal component regression (PCR), linear partial least squares (PLS), nonlinear principal component regression based on nonlinear iterative partial least squares algorithm (NIPALS-PCR) and nonlinear partial least squares based on nonlinear iterative partial least square algorithm (NIPALS-PLS) were used to determine the relationship between the quality and process variables. Time-series expansion methods were used to trace the dynamic behaviour based on five approaches, namely static, moving window (MW), recursive window (RW), exponentially weighted moving window (EWMW) and exponentially weighted recursive window (EWRW). The findings show that the combination of the linear prediction model with the time-series expansion method showed a more reliable prediction performance than the nonlinear prediction model. The performance of the PCR EWMW model in predicting the RBDPO quality is improved by 12.02 % (11.96 % for free fatty acid, 6.92 % for moisture content, 16.13 % for iodine value and 13.01 % for colour) compared to other prediction models. The sensitivity of the regression coefficients was also improved where the regression coefficients fluctuated very smoothly and showed high convergence to zero value when using the PCR EWMW model. This shows that the implementation of the linear dynamic prediction model was better than the static prediction model. Therefore, the linear dynamic prediction model for quality prediction was the best for it has the greatest prediction improvement and showed a better trend of the regression coefficient.

ABSTRAK

Proses kawalan statistik multipembolehubah (MSPC) digunakan secara meluas untuk ramalan kualiti dan memantau kualiti dalam proses penapisan minyak sawit. Pada masa kini, kualiti minyak sawit yang ditapis, diluntur, dinyahbau (RBDPO) ditentukan berdasarkan hubungan di antara kualiti minyak sawit mentah dan parameter proses dengan andaian proses tersebut adalah statik dan tidak dipengaruhi oleh ciri berbeza-beza semasa proses penapisan minyak sawit. Namun begitu, ramalan tersebut kurang tepat memandangkan pekali regresi yang dihasilkan daripada model ramalan statik itu tidak menggambarkan status proses semasa dan kekal malar sepanjang masa. Justeru, kajian ini dijalankan bagi memperkenalkan satu kerangka baharu untuk peningkatan pekali regresi melalui model ramalan dinamik. Model ramalan dinamik dibangunkan dengan mengintegrasikan alat ramalan MSPC dengan kaedah siri masa berkembang, dengan itu model ramalan dapat disesuaikan ke dinamik proses baharu. Data dikumpulkan dari loji industri penapisan minyak sawit digunakan sebagai kajian kes dalam penyelidikan ini. Empat model MSPC, iaitu regresi komponen utama linear (PCR), regresi kuasa dua terkecil separa linear (PLS), regresi komponen utama bukan linear berdasarkan algoritma regresi kuasa dua terkecil separa bukan linear (NIPALS-PLS) dan regresi kuasa dua terkecil separa bukan linear berdasarkan algoritma regresi kuasa dua terkecil separa bukan linear (NIPALS-PLS) digunakan untuk menentukan hubungan di antara pembolehubah kualiti dan pembolehubah proses. Kaedah pengembangan siri masa digunakan untuk menjejak tingkah laku dinamik berdasarkan lima pendekatan, iaitu statik, tetingkap bergerak (MW), tetingkap berkembang (RW), tetingkap bergerak berwajaran secara eksponen (EWMW) dan tetingkap berkembang berwajaran secara eksponen (EWRW). Hasil kajian mendapati kombinasi antara model ramalan linear dengan kaedah pengembangan siri masa menunjukkan prestasi ramalan yang lebih dipercayai berbanding model ramalan bukan linear. Prestasi model PCR EWMW dalam meramal kualiti RBDPO bertambah baik dengan 12.02 % (11.96 % bagi asid lemak bebas, 6.92 % bagi kandungan kelembapan, 16.13 % bagi nilai iodin dan 13.01 % bagi warna) berbanding model ramalan yang lain. Kepekaan pekali regresi juga bertambah baik di mana pekali regresi berubah-ubah dengan linear dan menunjukkan penumpuan yang tinggi ke nilai sifar apabila menggunakan model PCR EWMW. Ini menunjukkan bahawa pelaksanaan model ramalan dinamik linear lebih baik berbanding model ramalan statik. Justeru, model ramalan dinamik linear bagi ramalan kualiti adalah yang terbaik dengan penambahbaikan ramalan yang besar dan menunjukkan tren pekali regresi yang lebih baik.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

MSPC	-	Multivariate Statistical Process Control
CPO	-	Crude Palm Oil
RBDPO	-	Refined Bleached Deodorized Palm Oil
PCR	-	Principal Component Regression
PLS	-	Partial Least Square
FFA	-	Free Fatty Acid
MOIST	-	Moisture Content
IV	-	Iodine Value
DOBI	-	Deterioration of Bleachability Index
NIPALS	-	Nonlinear Iterative Partial Least Squares
MW	-	Moving Window
RW	-	Recursive Window
EWMW	-	Exponentially Weighted Moving Window
EWRW	-	Exponentially Weighted Recursive Window
MAE	-	Mean Absolute Error
UMBRAE	-	Unscaled Mean Bounded Relative Absolute Error
ANN	-	Artificial Neural Network
PCA	-	Principal Component Analysis
CLT	-	Central Limit Theorem
ACF	-	Autocorrelation Function
CCF	-	Cross-correlation Function
USL	-	Upper Specification Limit
LSL	-	Lower Specification Limit
PFAD	-	Palm Fatty Acid Distillate

LIST OF SYMBOLS

X	-	Data set
$\bar{X}$	-	Mean of data set
N, n	-	Number of data in a data set
Σ	-	Standard deviation
T	-	Time shift
Z	-	Z-score
H	-	Number of lag
μ	-	Average value
C_p	-	Capability ratio
C_{pk}	-	Capability index
C_{pu} ,C_{pl}	-	Capability with one-sided specification
T	-	Score matrix
P	-	Loading matrix
B	-	Coefficient matrix
U	-	Score matrix for output variable
Q	-	Loading matrix for output variable
Y	-	Actual value of output variable
$\hat{y}$	-	Predicted value of output variable
E	-	Deviation error
°C	-	Degree celcius
k	-	Regression coefficient
λ	-	Smoothing constant

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter explains the purpose and content of the research. This chapter includes the research background, problem statement, research objectives, scope of research, and the significance of study and layout of the thesis.

1.2 Research Background

In today’s consumer-driven world market, the manufacturing industries’ ability to sustain maximum production efficiency and ensuring high product quality has become a great challenge. The whole manufacturing process has to operate at the minimum waste production, minimum cost of utilities and minimum reprocess of flawed product quality to maximise production. The traditional quality assurance process such as performing manual machinery checks are difficult to validate; hence the company looking for the side of caution and discarding more off-specification end products. The inconsistent end-product quality and time-varying process behaviour during the start-up process led to drag overall operational efficiency. To maintain the production of high standard product quality, modern manufacturing industries need to bring systematic quality control into existence by considering all parameters affecting the product quality. Hence, efficient quality prediction tools need to be developed such that the product quality can be predicted ahead of time.

Multivariate Statistical Process Control (MSPC) has gained broad manufacturing industries' applications for quality improvement (Lestander *et al.*, 2012). MSPC is a technique to monitor and control of a process using statistical method. The implementation of MSPC quality tool such as control chart allows the detection and correction of the process variation (Madanhire and Mbohwa, 2016). Therefore, this research aims to develop a reliable product quality prediction tool using the combination of MSPC and time-series expansion method to reduce the effect of process time-varying behaviour. This prediction tool's is developed to improve the predictor coefficient such that the quality can be predicted accurately and thus, reducing the production of off-specification end-products. A palm oil refinery process is chosen as the case study.

1.3 Problem Statement

The Crude Palm Oil (CPO) produced from palm oil mills undergoes physical refining, which consists of degumming, bleaching and deodorization processes to produce Refined Bleached Deodorized Palm Oil (RBDPO). Currently, the palm oil refining process has difficulties in predicting and maintaining the quality of RBDPO. The RBDPO quality is highly depending on the CPO quality and the process condition. For example, during rainy season, the moisture content and free fatty acid of CPO is increased, which eventually forced the refining plant to consume more utilities such as bleaching earth and steam in order to maintain the RBDPO quality. Hence, to ensure the exiting RBDPO quality meet the specified standards, most commercial refining plants opt to go for the reprocessing alternative, to rectify and refine the inferior product again, thus to prevent scrapping the product altogether.

During the reprocessing, the off-specification RBDPO quality, for example RBDPO with high colour quality will be reprocessed from the beginning of the refining process to adjust the quality accordingly. However, to reprocess the off-specification RBDPO, the manufacturing plants have to allocate a large amount of cost and processing time (Schweiger and Floudas, 2009). The recycle process consumed about 30 minutes to five hours, and the loss of profit was about RM 159,000.00 per hour, mainly due to the production cost and opportunity loss (Makky and Soni, 2014). Thus, by reducing the possibility of reprocessing, the refinery would save up to 10 % per day with average of two hours reprocessing per day. In brief, the inadequacy to determine the final quality of RBDPO leads to the delay of processing time and raises the processing cost.

Conventionally, the quality of RBDPO can only be validated and inspected once the end product exits the refining process. Although it was possible for laboratory analysts to determine the qualities via chemical analysis and operator have access to massive amounts of process data, the analysts still need some more time and expertise to analyse and integrate the information with the RBDPO quality. This in-depth research and statistical analysis are far beyond laboratory analysts' scope and the operator's work. Besides that, the quality adjustment is made based on the tacit knowledge of the plant's supervisor, which cannot be easily comprehended for other operators to conduct the process condition readjustment.

In order to improve the quality management in the refining plant, there is a need of a systematic quality prediction tool that can predict the RBDPO quality ahead of time using a statistical method. This quality prediction tool can reduce the dependence of reprocessing stream and transforming the tacit knowledge into a model which can be accessed and practised by other operators. Several quality prediction tools have been developed for palm oil refinery process. Rani and teams have developed a quality prediction tool for refining process based on the relationship between CPO quality and RBDPO quality only (Rani *et al.*, 2015). On the other hand, Sulaiman and Yusof (2015) have successfully predicted the refined palm oil quality based on the relationship between CPO quality, process parameter and RBDPO quality.

Although these two prediction models can predict the refined palm oil quality, the model is not robust since the models are developed with the assumption that the sample population's underlying behaviour is static and does not change over time (static prediction model). In static prediction model, the regression coefficients are generated only once through single regression model and remain constant over the time-series. The model does not adapt to new process dynamic, where the change of process condition and quality of raw material over the time is neglected. This causes the accuracy of the prediction to diminish over time. Hence, there is a need to develop predictor that is automatically adapted to new process dynamic by developing the regression coefficient through dynamic prediction model as suggested by Shao and Tian (2015).

In this study, the dynamic prediction model is developed through continuous learning of the process behaviour based on real time data in order to improve the prediction tools. The improved prediction tools are developed by integrating the information of CPO quality, process parameters and RBDPO quality, and implement the dynamic approaches known as time-series expansion method. In dynamic prediction model, the updated model combines the information from the original data with the data from a new sample to predict future data and allows the model to capture the changes in data behaviour over time. Through this study, the dynamic prediction model improves the regression coefficient through convergence to zero value and hence, reducing the probability of off-specification RBDPO production. By doing these, the palm oil refining plant can predict the incoming RBDPO quality such that the product quality can be systematically guaranteed, and thus optimal plant performance can be fine-tuned for better smooth running and productivity.

1.4 Research Objectives

This research aims to develop a framework of an adaptive prediction tool to optimize palm oil refining plant performance through the improvement of the RBDPO quality prediction. Therefore, to achieve the abovementioned aim, several objectives of this research have been planned, which are:

a. To develop an adaptive linear and nonlinear quality prediction framework that can predict the RBDPO quality from the CPO quality and process parameters.

b. To generate the regression coefficients between input and output variables using linear and nonlinear Multivariate Statistical Process Control (MSPC).

c. To compare the linear and nonlinear prediction models' performance by calculating the error of prediction and monitoring the control chart.

d. To compare the developed prediction models' process capability index and regression coefficient values that can produce the RBDPO quality within the quality specification.

1.5 Research Scopes

This research requires several knowledge, including the physical refining process of palm oil and its parameters, statistical process control approaches related to industrial big data analysis, and quality monitoring and prediction concepts. The research scopes have been identified and listed as follows:

a. Using data from a palm oil refinery plant located in Sabah, Malaysia as a case study.
b. Developing the quality prediction tool using MATLAB software.
c. Assessing the performance of the developed quality prediction tools. Prediction results obtained using MATLAB software was compared to the data from the refinery plant.
d. Selecting output variables of interest and input variable using the *reliefF* algorithm.
e. Determining the optimum sampling time using autocorrelation analysis.
f. Determining the optimum processing time using cross-correlation analysis.
g. Developing quality prediction tools using Principal Component Regression (PCR) and Partial Least Squares Regression (PLS), Nonlinear Iterative Partial Least Squares algorithm for Principal Component Regression (NIPALS-PCR) and Nonlinear Iterative Partial Least Squares algorithm for Partial Least Squares Regression (NIPALS-PLS).

h. Developing an adaptive prediction model using time-series expansion methods namely Moving Window (MW), Recursive Window (RW), Exponentially Weighted Moving Window (EWMW) and Exponentially Weighted Recursive Window (EWRW).

i. Using a monitoring chart to monitor the process change (process behaviour) over time for both actual and predicted output variables.

j. Measuring the error of deviation between actual and predicted output variables using Mean Absolute Error (MAE).

k. Comparing the performance of prediction models using Unscaled Mean Bounded Relative Absolute Error (UMBRAE).

l. Measuring the capability of the prediction models using process capability index.

1.6 Research Significance

This research is an excellent showcase of the practicality and significance of statistical process control and regressions as prediction techniques in terms of knowledge, technology, and community.

a. Contribution to knowledge.

The conventional quality prediction tools are developed by using linear regression model with the assumption the process behaviour is static and neglecting the change in the process condition and quality of raw material. For example, Sepuan (2017) has shown that the RBDPO quality can be forecasted using a linear static MSPC model based on the relationship between the quality of RBDPO and CPO only. The idea was further extended in this study by considering the refinery process's nonlinear and time-varying behaviour. This study improves the current quality prediction framework through the integration of nonlinear regression model with the dynamic approaches using time-series expansion methods. The regression coefficient is generated based on the relationship between the quality variables and process variables. This study also explores the possibilities of using normal statistical techniques to estimate parameters that are unable to acquire in-situ. For example, the sampling time can be optimized via auto-correlation analysis for the industrial analysts to sample the CPO and RBDPO accordingly, to give the best randomized results.

b. Contribution to the technology.

Through the statistical prediction of RBDPO quality via adaptive MSPC models, this study can, hopefully, provide aid for the industrial personnel, especially for palm oil refinery industries, by creating an automated system via conversion of tacit knowledge into machine learning. Tacit knowledge is the know-how and intuitive knowledge, gain from experience and practices, which is hard to communicate since the knowledge resides in the mind of the practitioner. This tacit knowledge can be transformed into a mathematical modelling via machine learning through artificial intelligence (AI) where the data from the supply chains, production lines, quality control are linked together to form a highly integrated and intelligent engine. In this case study, the CPO quality, process parameter and RBDPO quality information are integrated and statistically computed into a mathematical model based on the training data.

The monitoring chart developed from this adaptive prediction models provide the process insight and guidelines to the plant operators at the beginning of the refinery process. Action plans must be prepared to deal with any possible out-of-specification condition, specifically during high-quality specification production. Action plans such as identifying the time where outliers input is expected to come into the process, monitoring the outliers and actions for adjustment on the off-specification products, are therefore necessary to optimize the refinery process's efficiency.

Besides that, with the monitoring chart's aid, the operators’ schedule in operation can be efficiently managed where the plant manager can schedule the operators based on the product specification. For instance, the manager can schedule the junior operator, working during the production of low specification RBDPO quality with normal or in-control process behaviour. For normal high specification quality production, both senior and junior operators can be scheduled to monitor the process. When the chart detected several outliers during the production of high specification RBDPO quality, the senior operator should monitor the process, perform the necessary action plans, and bring the process in control.

c. Contribution to the community.

This study is also the pioneering initiative to improve the big data analysis in the palm oil refining industry using MSPC, which makes a significant contribution to the widespread use of quality management. Big data analytic is one of the technology advancement in the 4th Industrial Revolution (4IR) where technology implements human intelligence, such as thinking and learning through computers. For this case study, the data is integrated and analysed using predictive model, where the computer or program learns through data observation and identifying the pattern and trend of the process. Through the combination of artificial intelligent and big data analytic, the refining plant can find the optimal way to manufacture the RBDPO quality, and hence, improving the product quality.

With this study, any uncertainty that arose during palm oil refining production can be efficiently minimized to maintain and satisfyingly guarantee the high-quality palm oil product. This study covers the use of MSPC, industrial big data and knowledge work automation, which also innovation to the palm oil refinery industry.

1.7 Thesis Layout

This study focuses on implementing linear and non-linear MSPC models with the time-series expansion method to predict the RBDPO quality adaptively. The outline of the thesis was stated as follows:

Chapter 1, the Introduction chapter, provides the research topic, research objectives, and scopes of the study's research and significance.

Chapter 2, the Literature Review chapter, elaborates Multivariate Statistical Process Control (MSPC) through the scholarly articles related to the prediction and finding the gaps. To name a few, the reviewed articles included statistical analysis for time-series, regression methods, statistical process control, an overview of the palm oil process flow and the modelling of a refinery plant as the case study.

Chapter 3, the Methodology chapter, outlines the overall methodological framework and explains the procedures to conduct quality prediction for RBDPO quality.

Chapter 4, the Results and Discussion chapter discuss the results obtained after executing the complete methodological steps in Chapter 3. The results include the optimum sample size, optimum sampling time, optimum processing time, regression coefficients, monitoring chart, prediction models' capability, and mean absolute error calculation.

Chapter 5, the Conclusion and Recommendations chapter, provide closure to the research by summarizing the findings and highlighting the significance of the study. The limitation of the study was also acknowledged and recommendations were suggested to address the limitation in future study.

1.8 Summary

The first chapter of the thesis opens with the research background and describes the current issues in the refinery palm oil industry. This is followed by the objective and the scope of the research. The contribution of the study to the knowledge, technology and community are explained in the section on research significance. The chapter ends with the layout of the thesis.

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LIST OF PUBLICATIONS

Indexed Journal

1) Rashid, N. A., Mohd Rosely, N. A., Mohd Noor, M. A., Shamsuddin, A., Abd Hamid, M. K., and Ibrahim, K. A. (2017). Forecasting of Refined Palm Oil Quality using Principal Component Regression. *Energy Procedia*, 142, pp. 2977-2982. **(Indexed by Scopus)**

2) Rashid, N. A., Hoong, K. W., Shamsuddin, A., Mohd Rosely, N. A., Mohd Noor, M. A., Jin, K. W., Lee, M. H., and Abd. Hamid, M. K. (2020). Quality Prediction and Diagnosis of Refined Palm Oil Using Partial Correlation Analysis. IOP Conference Series: Materials Science and Engineering, 884, pp. 012-018. **(Indexed by Scopus)**