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RESEARCH PAPER

A Novel Methodology for Monitoring and Control of Non-Stationary Processes Using Model-based Control Charts (Case Study: bottomhole Pressure during Drilling Operations)

Mahdi Imanian[1], Aazam Ghassemi[2] & Mahdi Karbasian[*3]

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ABSTRACT
This study applies two methods for the monitoring and control of autocorrelated processes based on time series modeling. The first method involves the simultaneous monitoring of common and assignable causes. This method includes the application of five steps of data gathering, normality test, autocorrelation test, model selection, and control chart selection on all non-stationary process observations. The second method is a novel method for the separate monitoring and control of common and assignable causes. In this method, the process was divided into parts with and without assignable causes. The first method was greatly non-stationary for not separating common and assignable causes. The application of this method also implied that common causes were hidden in the process. The novel method used for the separate monitoring of common and assignable causes could turn the process into a stationary one, leading to identifying, monitoring, and controlling common causes without any interference from the assignable causes. The results showed that, unlike the first method, the second method could be very sensitive to the common causes; it could, therefore, suitably monitor, identify, and control both assignable and common causes. The current work aimed to use control charts to monitor and control the bottomhole pressure during the drilling operation.

KEYWORDS: *Statistical process control; Control chart; Autocorrelated process; Bit pressure; Kick.*

1. Introduction

One of the most dangerous phenomena in the oil industry is the oil and gas well blowout. Blowout occurs due to the inability to control the kick (sudden entering of fluid from the formation into the well) on time. One of the most recent oil well blowouts occurred in Rag-Sefid oil field in Iran, 2017, leading to two deaths and the injury of 6 other people. This oil well was finally controlled after 60 days, causing many injuries and severe financial and environmental damage [1].

In conventional drilling, observing signs such as a change in the flow rate of the drilling fluid and an increase in the mud volume inside the pit can help predict the kick. These signs can warn about the repeat of the kick in Managed Pressure Drilling (MPD) and Under Balanced Drilling (UBD). These signs have a time delay and, therefore, have a possibility of false alarm. Early Kick Detections (EKD) are the methods proposed for solving the aforementioned problems [1].

Based on the second law of thermodynamics, all processes tend toward increased entropy. This entropy affects the process output through common and assignable causes. It is possible to control common causes using Engineering Process Control (EPC) methods such as feedback controllers. Assignable causes are identified and eliminated using Statistical Process Control (SPC) methods such as control charts. Control and compensation of assignable causes using EPC instead of eliminating them by using SPC leads to dynamic changes in the process [2,3].

Among studies done in EPC for controlling the bit pressure, one can mention the study of Li et al. [1]. They used an L_1 controller to monitor the process and control bit pressure in two cases with and without assignable causes. The assignable cause for this process was the drill pipe

* Corresponding author: *Mahdi Karbasian*
mkarbasi@mut-esf.ac.ir

1. *Department of industrial engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran.*
2. *Department of mechanical engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran.*
3. *Department of industrial engineering, Malek-Ashtar University of Technology, Shahinshahr, Iran.*

connection, which led to wrongly measured bit pressure due to the incorrect operation of Mud Pulse Telemetry (MPT) when mud circulation in the well stopped. In this study, EPC became operational during assignable causes to compensate for any erroneous process output by altering adjustable inputs.

Figure 1 shows a method used to choose between SPC and EPC for the process control based on the costs and related adjustment errors, sampling rate, and measurement errors. This figure shows that the application of SPC could be advisable in the case of measurement errors [4].

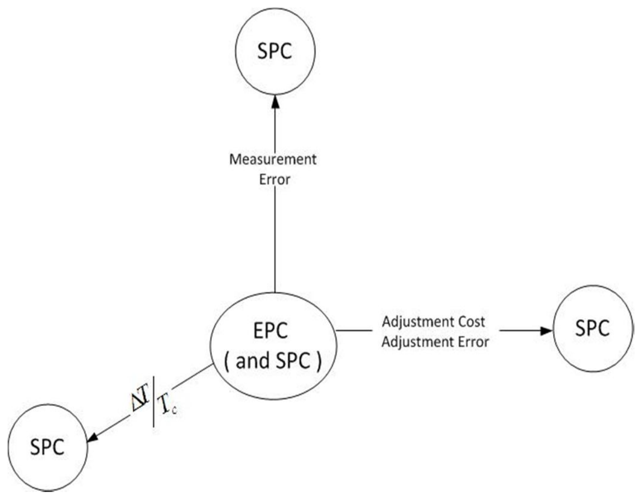

Fig. 1. Selection between SPC and EPC [4]

In order to implement SPC, constant monitoring of the process output is recommended to identify and eliminate assignable causes to reach a suitable process control method without any dynamic changes. One of the tools used for the continuous monitoring of bit pressure is MPT and Wired Drill-Pipe Telemetry (WDT) installed in the bit [5]. In oil well drilling, common causes include random diversions with sources hidden in the drilling operation. Assignable causes include diversions due to a source outside the drilling operation. An example of a common cause is the kick, while drill pipe connection, mud loss, or damaged or wrong measurement sensors are examples of the assignable causes. Therefore, it is possible to identify and control assignable causes without any change in the process dynamics by the constant monitoring of the bit pressure during operation using tools such as MPT and proper controllers [5]. After identifying the causes of deviation, it is possible to use the chock valve installed on the well's output path and on the weight and pressure of the drilling fluid to control the bit pressure and keep it as a set point.

According to Figure 2, drilling mud enters the well through a mud pump and drill string; it is transported to the surface after going through the annulus and exits through the choke valve. Bit pressure has the highest hydrostatic pressure during the drilling operation, which is used to control the bit pressure.

One of the conditions for using control charts is the independent nature of the measured data. Most chemical and industrial processes have autocorrelations between measured data, meaning that the application of control charts for process control leads to false alarms. One of the methods for reducing this autocorrelation and decreasing the rate of false alarms is the application of model-based methods. By identifying time series models of these processes, it is possible to calculate the residual value between the fitted model and the real data. Then, control charts are applied to these residual values to identify and eliminate assignable causes [6,7,8,9]. A brief history of studies regarding process monitoring control, especially in autocorrelated processes, is presented in the following section.

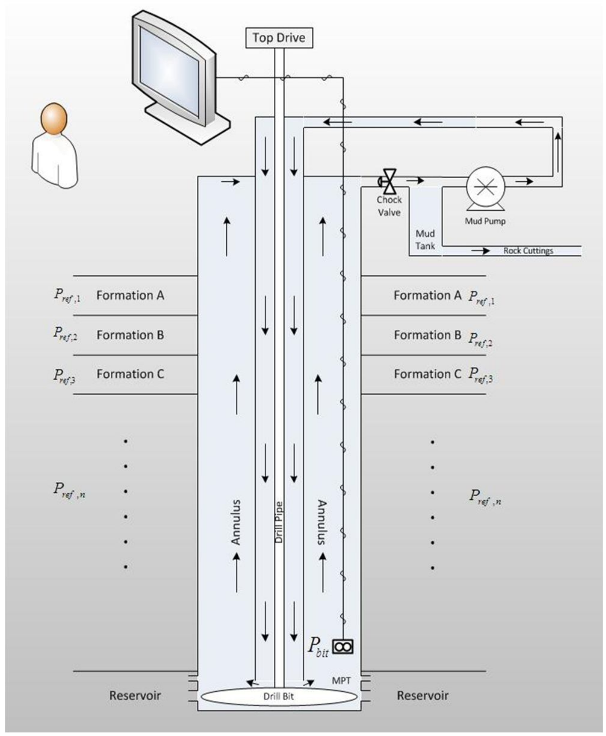

Fig. 2. The use of control charts for monitoring the bit pressure during the drilling operation [22]

Alipour and Noorossana [10] proposed a new fuzzy EWMA method for controlling MIMO processes and compared their results to fuzzy Hoteling control charts. Their results showed the superiority of FEWMA method. Similarly, Kazamzadeh et al. [11] used an EWMA control chart with different sampling intervals to monitor the process average based on ARL and ATS measures. Abouei Ardekan et al. [12] applied control charts and maintenance programs to propose a hybrid model. When control charts have faster warnings than maintenance programs, Reaction Maintenance (RM) was used and MEWMA control charts and maintenance models were compared and evaluated based on ARL measures.

Based on the previous literature, the application of control charts is proposed for monitoring bit pressure during drilling and identification of common and assignable causes. Therefore, this paper is divided into five sections. The first section provides an introduction to the bit pressure control and the use of control charts for autocorrelated processes. The second section presents simultaneous and separate methods for monitoring common and assignable causes in autocorrelated processes. The third section employs a case study of bit pressure during the drilling process to implement the methods presented in the previous section. The results are analyzed, discussed, and compared in the fourth section, and the reason for any deviations is investigated. Finally, the last section provides a conclusion and future suggestions for the monitoring and control of autocorrelated processes, especially bit pressure monitoring in oil well drilling.

2. Procedure

The necessary conditions for using control charts in a controlled process include independence and normality of observations with constant and known average (μ) and standard deviation (σ) values [13,14]. In these conditions, the process is shown using the following model, which is known as Shewhart model:

$$x_t = \mu + \varepsilon_t \qquad , \quad t = 1,2,..... \qquad (1)$$

In this equation, the observation at time t is shown by x_t. ε_t is independent and follows a normal distribution with $\mu = 0$, and σ is called white noise.

Under conditions of independent and normal observations, it is possible to use control charts for process monitoring and control. When there are changes in the values of μ and σ, process changes into an out-of-control state and the method for process identification, monitoring, and control changes. A five-step approach is used for proper process monitoring; it includes observations, normality test, autocorrelation test, model selection and control chart selection. The details of these steps are presented below [15].

2.1. Observation

Observation is the first step in this five-step approach. The proper selection of the measurement time period for sensors is important in process and chemical industries. Reducing sampling time increases autocorrelation and increases the time delay before the identification of common and assignable causes. On the other hand, it is important to ensure the accuracy of sensor measurements. In the case of measurement sensor faults, assignable causes are introduced into the process, thereby affecting measured data and creating an error in the identification of common causes in the process [2].

2.2. Normality test

The normality of the measured data is one of the conditions for using control charts. Borror et al. [16] used the ARL measure to evaluate Shewhart and EWMA charts for individual observations and observations with non-normal distribution. ARL measure is the average of the points before the observation of an alarm in the control chart. The important results of this work include:

1. Significant reduction in ARL occurs in the control under the individual observation of Shewhart chart with the increased false alarms due to non-normal observations.
2. In the case of the assumption of normal observations being wrong, it is possible to use EWMA chart with $\lambda = 0.05$ or $\lambda = 0.1$ and suitable control limits to achieve acceptable results.

Similar observations were reported by Shiau and Chen [17] about autocorrelated processes, confirming the necessity of low λ values for non-normal processes.

2.3. Autocorrelation test

One of the key assumptions of the use of control charts is that successive values of quality characteristics as they are observed through time are not correlated with each other. Modern manufacturing methods and sensor technologies often imply that quality data are serially correlated in time, and this can have a large impact on the performance of control charts [4].

Shiau and Hsu [17] investigated the effects of positive autocorrelation on the results of control charts, suggesting the use of EWMA charts with high λ values for processes with low autocorrelation.

2.4. Model selection

One of the suitable methods for removing autocorrelation in the measured data is the model-based approach. In this approach, the time series model resulting from the autocorrelation between observations is determined and control chart is used for monitoring the residual between the real values (x_t) and the fitted time series model ($\hat{x}_t$). The residuals are calculated using $e_t = x_t - \hat{x}_t$, with no significant autocorrelation. Autoregressive (AR), Moving average (MA), their mixture or Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA) time series models are calculated using Box-Jenkins method [18]. In their work, Box et al. analyzed stationary and non-stationary time series based on probability theory and used the results to determine an optimum model for autocorrelated processes. Stationary models have a constant average and variance over time, while variance and average change with time in the non-stationary processes. AR, MA, and ARMA are the examples of stationary models, while ARIMA is the example of a non-stationary model. It is possible to use Difference Stationary Process (DSP) or Trend Stationary Process (TSP) to turn non-stationary models into stationary ones. The general format of time series ARIMA (p, d, q) models is as follows:

$$\Phi_p(B).\nabla^d.x_t = \Theta_q(B).\varepsilon_t \qquad (2)$$

In this equation: $\Phi_p(B) = \left(1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p\right)$ is the autoregressive polynomial of the $p-th$ order, $\Theta_q(B) = \left(1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q\right)$ is the moving averages polynomial of the $q-th$ order, ∇ represents backward, d is the difference order, t represents time, B is the backshift operator $B.x_t = (x_{t-1})$, $\phi_1, \phi_2, ..., \phi_p$ - refer to the parameters of the autoregressive model, $\theta_1, \theta_2, ..., \theta_q$ - are the parameters of moving averages model, and ε_t is called white noise.

It is possible to use Autocorrelation Function (ACF) to determine the suitable P value for MA and use Partial Autocorrelation Function (PCF) to determine the value of q for AR in time series.

Another method for determining p and q orders is the use of Augmented Dickey Fuller (ADF) test with the null hypothesis of existing unit roots and Schwarz's Bayesian information criterion (SBIC), Akaike's information criterion (AIC), and Hannan-Quinn Information Criterion (HQC). This method creates a table based on p and q values and fills them with each of the SBIC, AIC, or HQC criteria. Then, the suitable model is selected based on the lowest value of this table.

The d order is determined based on the unit root test. For example, by using ADF test and confirming the null hypothesis at the determined confidence level, the process is non-stationary. By implementing the DSP process, differentiating order (d=1), and repeating the ADF test, it is possible to achieve a stationary process. If a stationary process is not achieved, it is possible to increase the d value until a stationary process is reached.

2.5. Control chart selection

After investigating the normalization and autocorrelation of the measured data, a suitable control chart is selected to monitor and control the common and assignable causes of the process. Selecting a suitable control chart is carried out based on criteria such as normalization of observations, types of causes, observation types, the measured values, and the observed autocorrelation level.

Control charts are divided into two types: with and without memory. Charts without memory simply use the data from the current time for process monitoring. Shewhart charts are an example of these charts. Charts with memory use current and part data for process monitoring and include examples such as EWMA and CUSUM charts [2].

Shewhart [19] first proposed Shewhart charts for process monitoring. These control charts are suitable for monitoring assignable causes; however, they lack the necessary sensitivity for monitoring common causes. This led to the introduction of CUSUM charts by Page [20] and EWMA charts by Roberts [21] to monitor common causes. EWMA and CUSUM charts had comparable performances; however, in this work, EWMA charts were used for process monitoring due to their simplicity.

Table 1 shows the statistics and control limits of Shewhart and EWMA charts. In this table, μ is the target mean, σ is the standard deviation, L is the width control limit factor, λ is the smoothing parameter, and Z_i is the EWMA statistics.

Tab. 1. Statistics and control limits of the control charts.

Control Chart	Statistics	Control Limits
Shewhart	X_i	$\mu_0 \pm 3\sigma$
EWMA	$Z_i = \lambda x_i + (1-\lambda)Z_{i-1}$	$\mu_0 \pm L\sigma\sqrt{\frac{\lambda}{2-\lambda}\left[1-(1-\lambda)^{2i}\right]}$

Figure 3 shows the five-step process of process identification, monitoring and control based on the explanations given in this section.

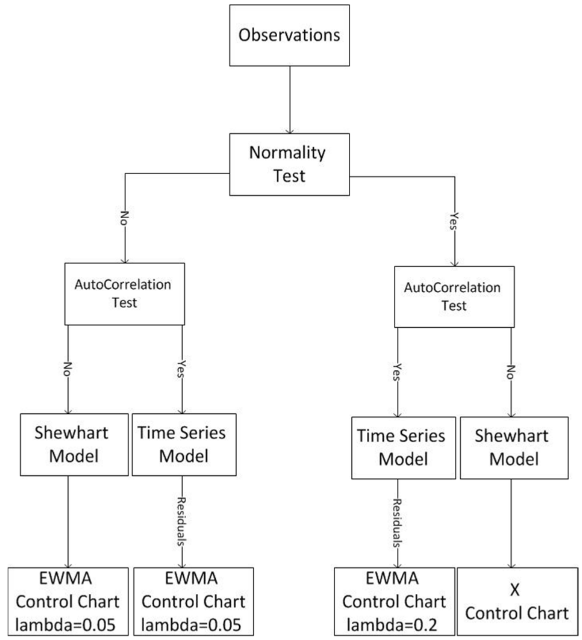

Fig. 3. Five steps of process identification, monitoring, and control.

2.6. New methodology

During autocorrelated observations, we should ensure that this autocorrelation is an intrinsic part of the process itself, not the result of the assigned causes. This requires a full understanding of the process under study. This type of autocorrelation takes place in chemical and industrial processes characterized by enough process knowledge to determine that assigned variations can help reduce autocorrelation [2].

By identifying the time period of assigned process variations, it is possible to divide the process into two parts: with and without assigned variations. Then, the five steps of process identification, monitoring, and control can be separately applied to both parts. Unlike the method that simultaneously monitors common and assigned causes, this method significantly reduces process autocorrelation, changes the process from non-stationary to a stationary process, and can identify, monitor, and control common causes without any effects from the assigned causes. By implementing the separate monitoring of common and assigned causes, it is possible to select control charts suitable for the variations of each part and significantly reduce the number of false alarms.

In the next section, both simultaneous and separate identification, monitoring, and control of common and assigned causes based on the five-step approach are implemented in a case study of bit pressure during drilling operation, and their performance is compared based on the reduction of autocorrelation and the increased stationary nature of the process.

3. Results

In order to evaluate the trends observed in the current study, the data presented in the paper by Nikoofard et al. [5] on Drill Pipe Connection in a UBD process were used. These data were recorded using a WDT during the drilling of an oil well from fluid pressure inside the bit at 1-minute time intervals. In this process, in order to add the drill pipe to the drill string, the line between the mud pump and the well was disconnected during drilling, and the pressure sensor did not function ideally. This means that bit pressure has a measurement error that creates an assignable cause. On the other hand, in the UBD process, in order to increase the drilling speed, the weight of the mud injected into the well was light enough to keep mud column pressure near the formation pressure. As a result, this process had a higher probability of kick than overbalanced drilling, especially at deeper depths. This means that monitoring bit pressure during a process would become more important with an increase in depth. In this case study, the simultaneous and separate monitoring of the assigned (drill pipe connection) and common causes (kick) was carried out at a depth of $2530 \pm 10m$. The drill pipe connection process was implemented in two parts at times $t = 1hr50\min$ and $t = 3hr35\min$ for 15 minutes each time. The total length of the process was 5 hours and 30 minutes.

In this wok, the identification, monitoring, and control of the process were carried out using two approaches mentioned in the previous section. In the first approach, assignable and common causes were simultaneously monitored, and all data were measured at 1-minute time intervals (330 total observations) together (a). In the second approach, i.e., the separate monitoring of assignable and common causes, the process was divided into five parts and each part was monitored separately. These five parts included (b) before the first drill pipe connection (first 95 minutes), (c) during the first drill pipe connection (15 minutes), (d) after the first drill pipe connection and before the second drill pipe connection (105 minutes), (e) during the second drill pipe connection (15 minutes), and (f) after the second drill pipe connection (100 minutes).

The five steps of Figure 3 were applied to each part of each approach. In the normality test step, Anderson-Darling Normality test at a confidence interval of 95% was used. When normality test showed that the process was normal, in order to increase the confidence about data normality, histogram graphs were created. In the autocorrelation test step, ACF and PCF were drawn at different intervals. In the model selection step, first, the stationary or non-stationary nature of the autocorrelated process was determined using the Unit Root Tests at a 95% confidence interval (table 2). Afterwards, a suitable Shewhart time series was selected based on the previous steps. This step used the Box-Jenkins method proposed by Box et al. [18] to determine the suitable time series. In the control chart selection step, Shewhart control chart was used for normal processes without autocorrelation, while EWMA control charts with $\lambda = 0.05$ were used for the monitoring and control of non-normal and autocorrelated processes. On the other hand, in the case of autocorrelation with one gap in the normal processes, EWMA charts with $\lambda = 0.2$ were used. All steps, methods, and parts of the above procedure were carried out using Minitab 16, Statgraphics 18 statistical applications, and Eviews 10 econometrics application, with the inputs presented in Tables 2 to 3 and Figures 4 to 9. The analysis results are discussed in the next section.

4. Discussion

In the previous section, identification, monitoring, and control of the bit pressure during the drilling operation were carried out using two approaches. Figure 4 shows the normality test, autocorrelation test, and the control chart of the observations before model fitting and on residuals after model fitting for the first method that attempted to identify, monitor, and control the process using all observations and residuals without separating common and assignable causes. The results of unit root test for this method confirmed that this process was non-stationary. The results of ADF and PP tests by this method are presented in the first and second lines of Table 2, showing the results before and after differentiation, respectively. As can be seen, the process reached stationary conditions after one step of differentiation; therefore, based on Box-Jenkins method, ARIMA (1,1,0) time series was selected for this process. The fitted model is provided in Table 3 (a). Figures 4(a) and 4(b) show non-normal observations and residuals before and after fitting the time series model. Figure 4(c) shows ACF for different lags depicting the serial autocorrelation before fitting the time series model. This function determines the number of q lags for MA series. Figure 4(d) shows the elimination of this autocorrelation in residuals after fitting the time series model. Figure 4(e) shows PCF for different lags and autocorrelation in observations before model fitting. This function determines the number of p lags of AR time series. Figure 4(f) shows the elimination of this autocorrelation in residuals after fitting the time series model. Figure 4(g) shows the EWMA control chart for observations before fitting the time series. Due to the high autocorrelation between observations, the number of out-of-control points was high, showing an unacceptably high number of false alarms. To solve this problem, EWMA control chart was applied to residual values after fitting the time series, as shown in Figure 4(h). Due to the non-normality of observations and residuals, based on the guideline shown in Figure 3, the value of $\lambda = 0.05$ was selected. According to Figure 4(h), 12 observations in the first pipe connection and 4 observations in the second pipe connection were out of control, showing false alarms for the assignable causes. This method was unable to monitor common causes, because assignable causes affected common causes. In addition, they could hide them during process monitoring. As a result, kick occurrence, which is a common cause, could not be monitored and identified. The presence of assignable causes also meant that the process was significantly non-stationary, adding one step to the five steps required for identification, monitoring, and control. This added step was required to make the process stationary and, as a result, could increase the monitoring time.

The above-mentioned method was used for the simultaneous monitoring of common and assignable causes. In order to fix the problems with this approach, a second approach for the separate monitoring of common and assignable causes was used. By identifying the time of assignable causes (during drill pipe connection), it was possible to divide the process into parts with and without assignable causes. For example, this process could be divided into five parts where the first, third, and fifth parts would lack assignable causes, as shown in Figures 5, 7, and 9, respectively. The second and fourth parts include assignable causes that are shown in Figures 6 and 8, respectively.

The results of the unit root test for the first, third, and fifth parts of the process proved the stationary nature of the process in these parts. The results of ADF and PP tests for these three parts are presented in the third, fourth, and fifth lines of Table 2. Based on Box-Jenkins method, ARIMA (1,0,0), ARIMA (1,0,1), and ARIMA (1,0,1) time series were selected for the first, third, and fifth parts of the process, respectively. The fitted models are provided in Tables 3(b), 3(d), and 3(f). Figures 5(a), 7(a), and 9(a) also show the non-normality of observations before fitting the time series, while Figures 5(b), 7(b), and 9(b) represent the non-normality of residuals after fitting the time series. Figures 5(c), 7(c), and 9(c) represent ACF in different lags, showing serial autocorrelation before fitting the time series model. Figures 5(d), 7(d) and 9(d) show the elimination of this autocorrelation after fitting the time series models. Figures 5(e), 7(e), and 9(e) also show PCF at different lags, as well as the autocorrelation of observations before fitting the time series model. Figures 5(f), 7(f), and 9(f) display the elimination of these autocorrelations in residuals after fitting the time series model. Figures 5(g), 7(g), and 9(g), on the other hand, show the EWMA control charts on observations before fitting the time series. Due to the high autocorrelation, the number of uncontrolled points was high, showing unacceptably high false alarms in these charts. In order to fix this problem, EWMA control charts were applied to the residual values after fitting the time series, as shown in Figures 5(h), 7(h), and 9(h). Due to the non-normality of observations and residuals, based on the guideline shown in Figure 3, the value of $\lambda = 0.05$ was selected. In the control chart shown in Figure 7(h), which belongs to the first part of the process, only the last two observations were below the lower control limit. In this section, the mud pump was turned off in preparation for the pipe connection operation. After turning off the mud pump, the opening of the chock valve changed from 10% to 6% so that a lower amount of fluid left the well. In other words, turning off the mud pump decreased bit pressure, and closing the chock valve increased the bit pressure again. These two uncontrolled points were due to the time delay before the pressure reached an optimum value of 235bar. Any delay to take actions in order to preserve bit pressure in the optimal range increased the probability of kick due to the UBD operational conditions. In the control chart shown in Figure 7(h) for the third part, after the first pipe connection procedure, a total of 4 points were out of control. The reason for these points was to add the drill pipe to the drill string that increased the well volume and, therefore, decreased the pressure of the mud column. By turning on the mud pump and renewing the fluid flow into the well, this empty space was gradually filled, leading to an increasing trend at the bit pressure. This increase continued until the 131st minute (the 21st observation in this part), leading to one uncontrolled observation. After reconnecting the mud pump, the chock valve returned to its original opening of 10%. Due to the higher time delay in the chock valve, as compared to mud pump, this increasing trend changed into a decreasing one after the 131st minute until the time of the second pipe connection. The evaluation of the chart shown in Figure 9(h) for the fifth part of the process after the second pipe connection was similar to the previous ones. The only difference was that, in this part, the number of out-of-control points was higher than that in the third part. This resulted from an increase in the well's depth and volume; therefore, a greater reduction in the bit pressure after the second pipe connection occurred, as compared to the first pipe connection. It is worth noting that the chock valve changed from 10% to 5% in the second pipe connection due to the greater bit pressure drop in the second pipe connection as a result of the increased well depth and well volume.

The second and fourth parts of the process showed the first and second pipe connections, respectively. Figures 6(a) and 8(a) show the non-normality of observations in the second and fourth parts, according to Anderson-Darling Normality test, at a confidence interval of 95%. In order to ensure the normality of observations, the histograms of these two parts are shown in Figures 6(b) and 8(b). After ensuring the normality of observations, the autocorrelation of observations, according to ACF, is shown in Figures 6(c) and 8(c), while autocorrelation according to PCF is shown in 6(d) and 8(d). The process had negligible autocorrelation in the first lag of both parts. As a result, due to the normal nature of observations and their negligible autocorrelation, the Shewhart control chart was applied to the observations in Figures 6(h) and 8(h). Compared to Shewhart charts, EWMA control charts with $\lambda = 0.05$, 0.1, and 0.2 are also shown in Figures 6(e), 8(e), 6(f), 8(f), 6(g), and 8(g), respectively. The evaluation of EWMA charts with different λ values showed that with an increase in λ values, the number of out-of-control points, out of upper control limits, and out of lower control limits became more similar to the Shewhart chart. It is worth mentioning that the out of control nature of the process in these two parts was due to the assignable causes as a result of the pipe connection.

5. Conclusion

In this work, for the first time, two different approaches including simultaneous and separate monitoring of common and assignable causes using control charts based on modeling were used to control the bit pressure during the drilling operation. Both approaches included five steps of observation, normality test, autocorrelation test, model selection, and control chart selection.

In the first approach, which is known as the simultaneous monitoring of common and assignable causes, without removing the assignable causes due to the drill pipe connection, process monitoring and control were carried out. In this approach, the presence of assignable causes masked common causes, making it impossible to control common causes. The presence of assignable causes in the autocorrelated process also made it non-stationary, which lengthened the monitoring and control process. One of the assumptions on the use of control charts is the stationary process. As a result, changing a non-stationary process to a stationary one would require procedures such as differentiation or trend elimination.

In order to fix the above problems, the second approach monitored the assignable and common causes separately. In this novel approach, an autocorrelated, non-stationary process was divided into parts with and without assignable causes before using five steps of process identification, monitoring, and control. The application of this approach in the bit pressure control during the drilling operation could significantly reduce the autocorrelation between observations, turning the process from a non-stationary process to a stationary one. This new approach would require process knowledge to determine the timing of assignable causes. In monitoring the bit pressure during the drilling operation, the process was divided into five parts including (1) before the first drill pipe connection, (2) during the first drill pipe connection, (3) after the first drill pipe connection and before the second drill pipe connection, (4) during the second drill pipe connection, and (5) after the second drill pipe connection.

The first, third, and fifth parts of the process were non-normal and lacked autocorrelation between residuals; therefore, EWMA control charts with $\lambda = 0.05$ were used. The opening of the chock valve was determined based on the increasing or decreasing trend of these charts and out-of-control points before and after pipe connection in order to adjust bit pressure and prevent kick occurrence. The charts drawn for the first, third, and fifth parts showed that pipe connection at deeper depths led to a greater increase in chart's slope and the number of out-of-control observations before and after pipe connection. This was due to the enhanced well volume with an increase in the drilling depth, leading to an increase in the volume of drilling mud necessary to compensate for the poor pipe connection. This increased pressure drop could be compensated by closing the chock valve.

In the second and fourth parts, due to the normal operation and negligible autocorrelation, Shewhart control charts were used. In these parts, EWMA charts with different values of λ were also used and compared with the results of Shewhart charts. Due to the negligible autocorrelation of the process, EWMA charts with higher λ values could be more similar to Shewhart charts. This second approach could be, therefore, useful to identify common and assignable causes and prevent kick during the Under Balanced Drilling (UBD) operation.

The results showed that, unlike the first approach, the second approach could be very sensitive to common causes; it could, in fact, identify, monitor, and control both assignable and common causes. Future studies can, therefore, apply EPC methods along with SPC for the control and compensation of common causes in this process.

Tab. 2. Unit root tests for selecting the suitable models

Unit Root Tests	Null Hypothesis: P has a unit root (Not Stationary) / 95% Confidence Interval							
	ADF						PP	
	SIBC		AIC		HQ			
	t-Statistic	Prob	t-Statistic	Prob	t-Statistic	Prob	t-Statistic	Prob
P	-2.089863	0.2490	-3.32712	0.145	-2.258090	0.1865	-2.370564	0.1510
D(P)	-11.66116	0	-5.666884	0	-8.684742	0	-12.27158	0
P , Part A	-5.264040	0.0175	-5.618565	0.0160	-5.264040	0.0175	-5.309950	0.0118
P , Part C	-3.152451	0.0259	-3.152451	0.0259	-3.152451	0.0259	-3.100751	0.02449
P , Part E	-7.164552	0	-7.012696	0	-7.012696	0	-7.232953	0

Tab. 3. Model selection step of the five-step procedure for process identification, monitoring, and control.

(a) First approach
(b) Second approach, the first part before the first drill pipe connection
(c) Second approach, the second part during the first drill pipe connection
(d) Second approach, the third part after the first drill pipe connection and before the second drill pipe connection
(e) Second approach, the fourth part during the second drill pipe connection
(f) Second approach, the fifth part after the second drill pipe connection

P Time Duration : 330 min	Time Series Model / ARIMA(1,1,0) $D(P_t) = -0.019151256362 + 0.410315449263 D(PA_{t-1}) + \varepsilon_t$
P , Part A Time Duration : 95 min	Time Series Model / ARIMA(1,0,0) $PA_t = 235.012779582 + 0.990867765409 PA_{t-1} + \varepsilon_t$
P , Part B Time Duration : 15 min	Shewhart Model $PB_t = 223.547 + \varepsilon_t$ First Drill Pipe Connection
P , Part C Time Duration : 105 min	Time Series Model / ARIMA(1,0,1) $PC_t = 225.590582228 + 0.990607351216 PC_{t-1} + \varepsilon_t + 0.343811975323 \varepsilon_t$
P , Part D Time Duration : 15 min	Shewhart Model $PD_t = 228.039 + \varepsilon_t$ Second Drill Pipe Connection
P , Part E Time Duration : 100 min	Time Series Model / ARIMA(1,0,1) $PE_t = 231.03607532 + 0.989592980212 PE_{t-1} + \varepsilon_t + 0.338513954131 \varepsilon_{t-1}$

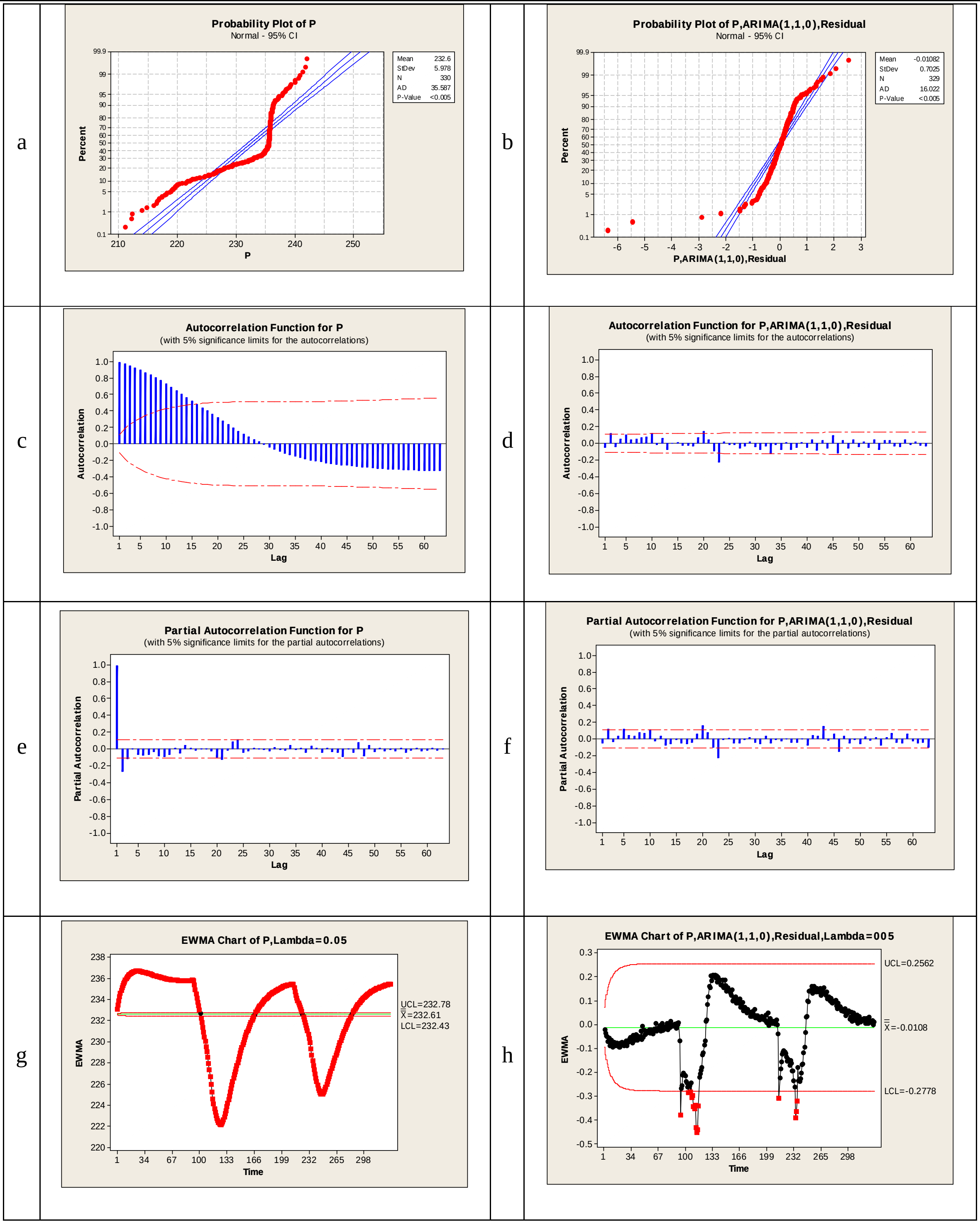

Fig. 4. Normality test, Autocorrelation test, and Control chart selection steps of the five-step procedure for process identification, monitoring, and control for the first approach

(a) Normality test on the measured observations (before model selection)
(b) Normality test on residuals (after model selection)
(c) Autocorrelation Test (ACF) on the measured observations (before model selection)
(d) Autocorrelation Test (ACF) on residuals (after model selection)
(e) Autocorrelation Test (PCF) on the measured observations (before model selection)
(f) Autocorrelation Test (PCF) on residuals (after model selection)
(g) Control chart for the measured observations (before model selection)
(h) Control chart for residuals (after model selection)

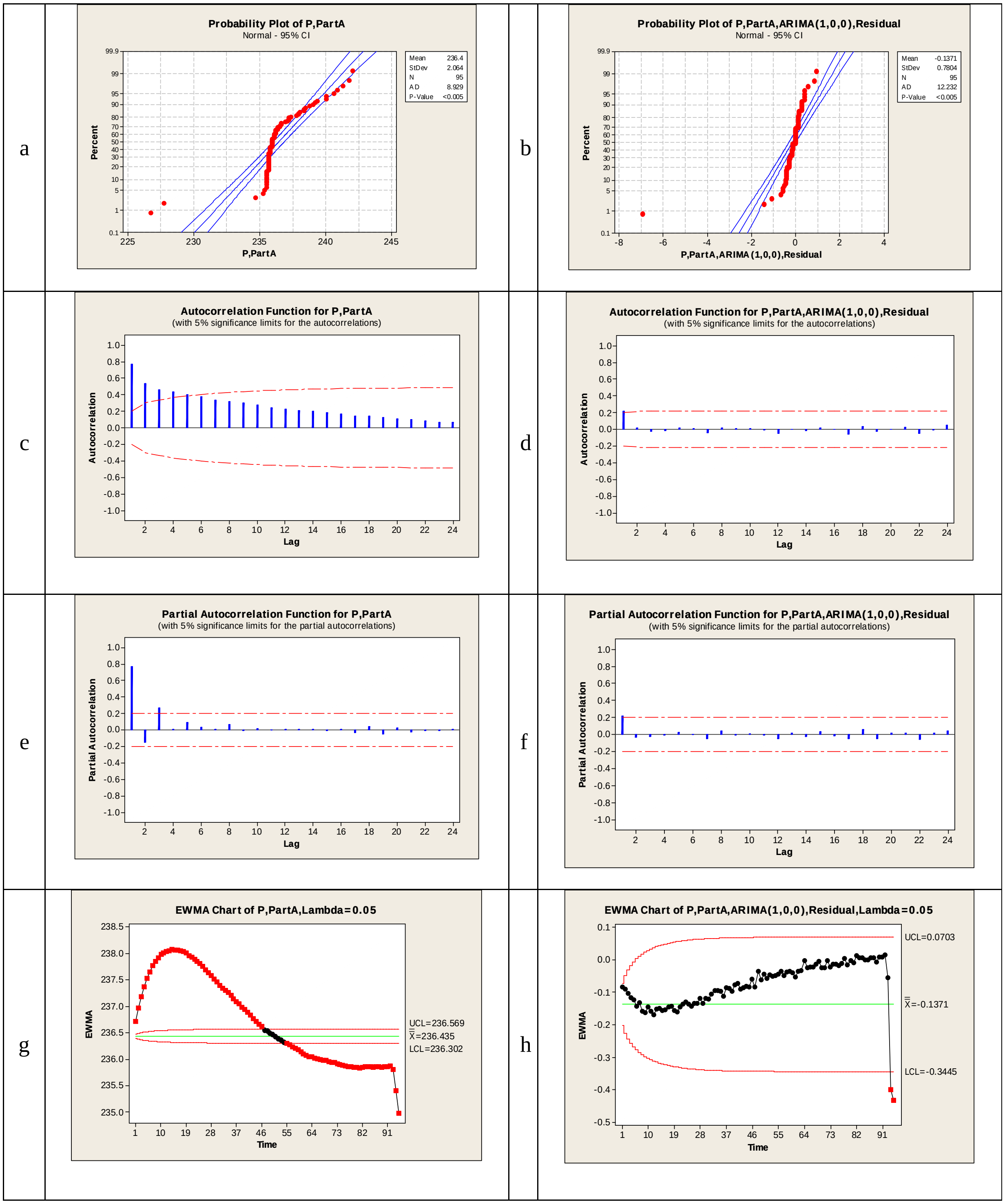

Fig. 5. Normality test, Autocorrelation test, and Control chart selection steps of the five-step procedure for process identification, monitoring, and control for the second approach, the first part

(a) Normality test on the measured observations (before model selection)
(b) Normality test on residuals (after model selection)
(c) Autocorrelation Test (ACF) on the measured observations (before model selection)
(d) Autocorrelation Test (ACF) on residuals (after model selection)
(e) Autocorrelation Test (PCF) on the measured observations (before model selection)
(f) Autocorrelation Test (PCF) on residuals (after model selection)
(g) Control chart for the measured observations (before model selection)
(h) Control chart for residuals (after model selection)

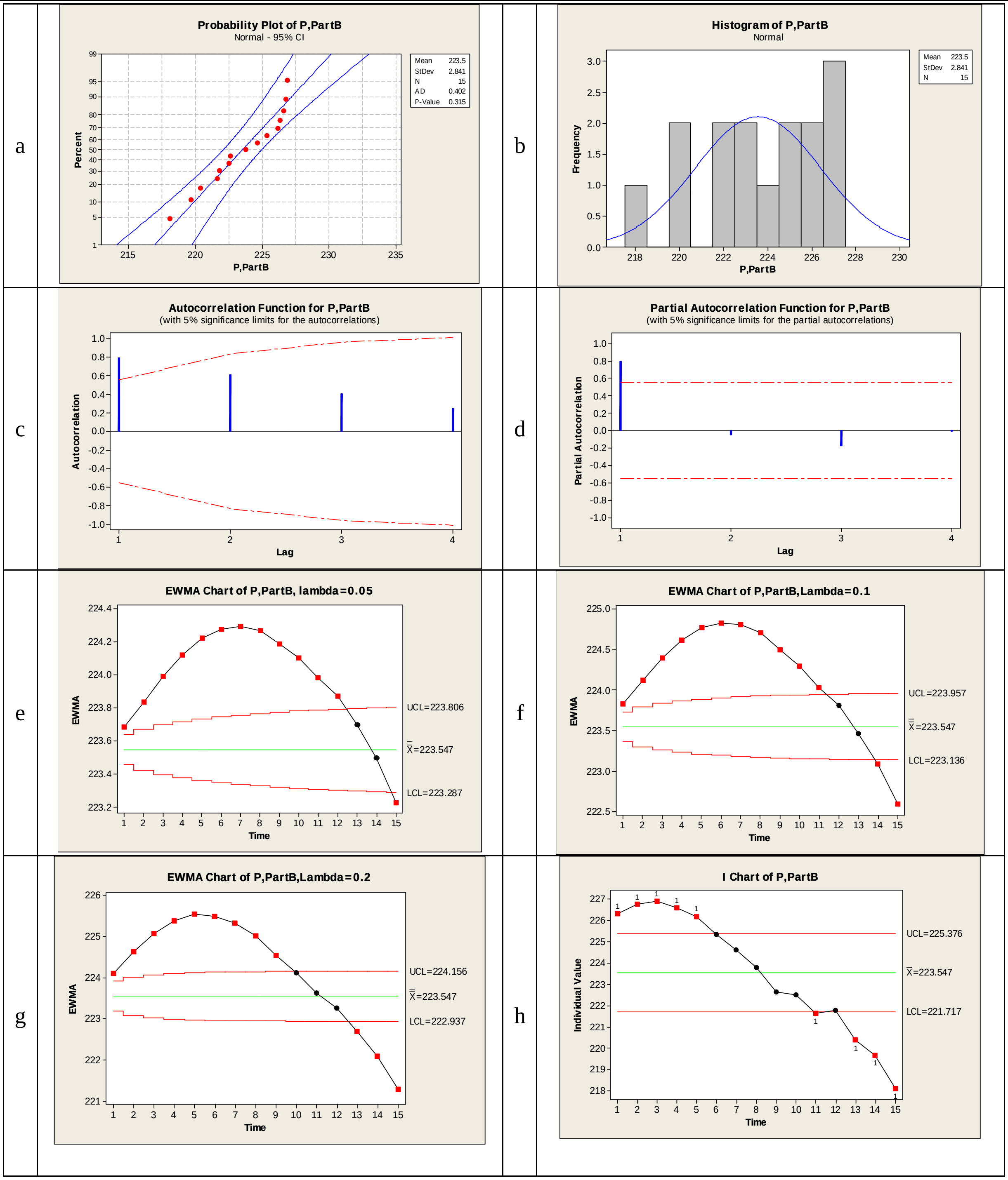

Fig. 6. Normality test, Autocorrelation test, and Control chart selection steps of the five-step procedure for process identification, monitoring, and control for the second approach, the second part

(a) Normality test on the measured observations (probability plot)
(b) Normality test on the measured observations (histogram)
(c) Autocorrelation test (ACF) on the measured observations
(d) Autocorrelation test (PCF) on the measured observations
(e) Control chart for the measured observations (EWMA, $\lambda = 0.05$)
(f) Control chart for the measured observations (EWMA, $\lambda = 0.1$)
(g) Control chart for the measured observations (EWMA, $\lambda = 0.2$)
(h) Control chart for the measured observations (Shewhart)

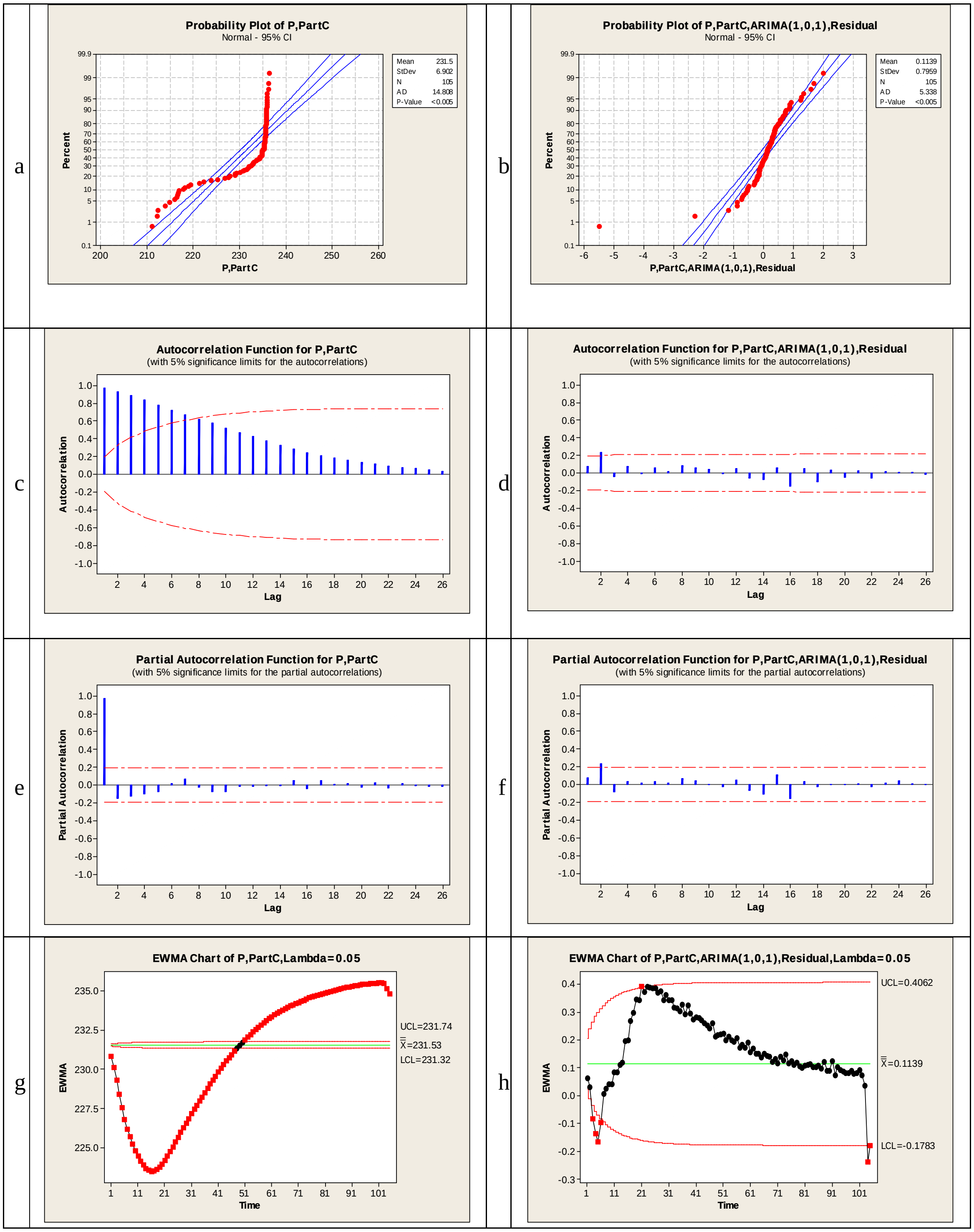

Fig. 7. Normality test, Autocorrelation test, and Control chart selection steps of the five-step procedure for process identification, monitoring, and control for the second approach, the third part

(a) Normality test on the measured observations (before model selection)
(b) Normality test on residuals (after model selection)
(c) Autocorrelation Test (ACF) on the measured observations (before model selection)
(d) Autocorrelation Test (ACF) on residuals (after model selection)
(e) Autocorrelation Test (PCF) on the measured observations (before model selection)
(f) Autocorrelation Test (PCF) on residuals (after model selection)
(g) Control chart for the measured observations (before model selection)
(h) Control chart for residuals (after model selection)

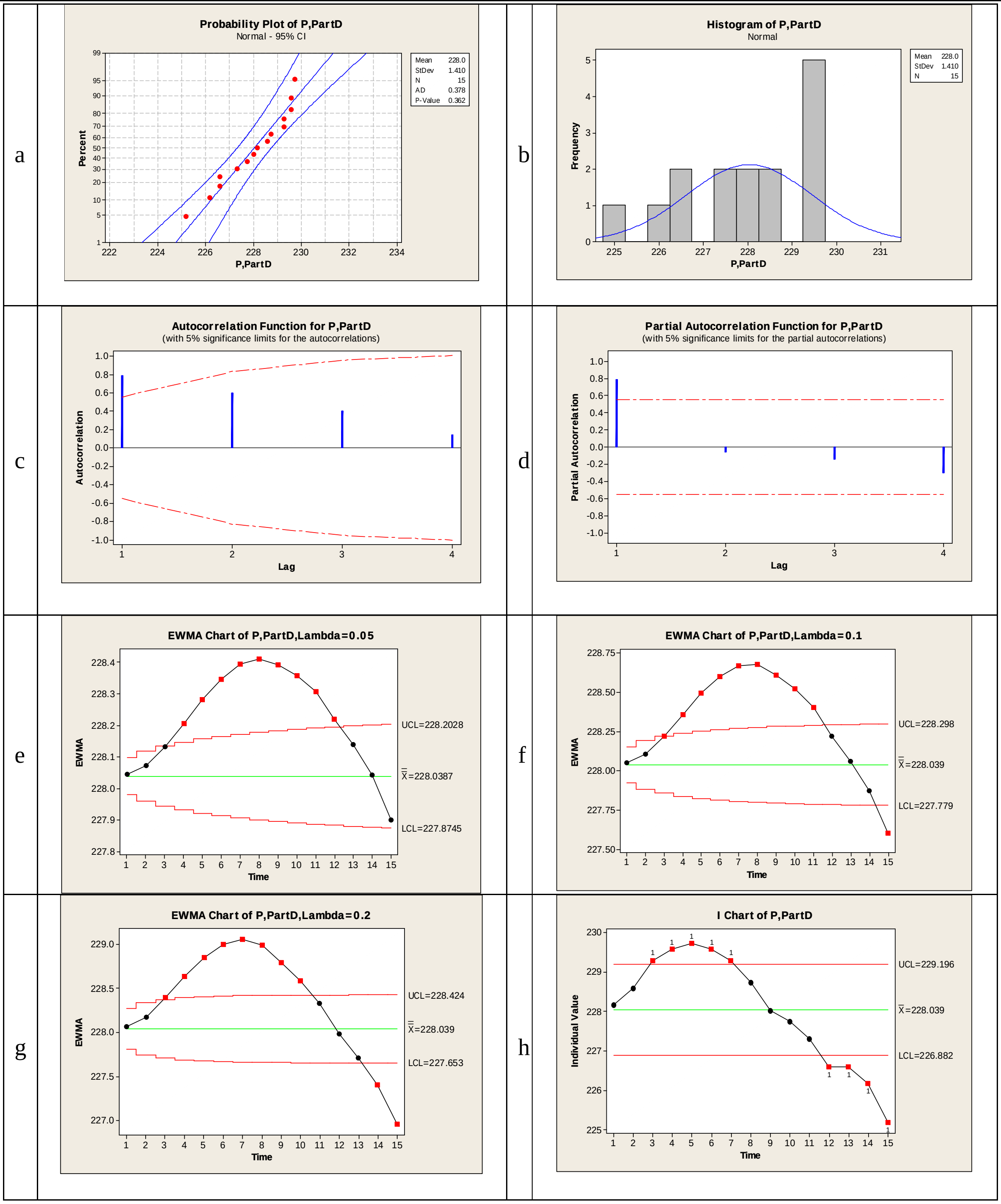

Fig. 8. Normality test, autocorrelation test, and control chart selection steps of the five-step procedure for process identification, monitoring, and control for the second approach, the fourth part

(a) Normality test on the measured observations (probability plot)
(b) Normality test on the measured observations (histogram)
(c) Autocorrelation test (ACF) on the measured observations
(d) Autocorrelation test (PCF) on the measured observations
(e) Control chart for the measured observations (EWMA, $\lambda = 0.05$)
(f) Control chart for the measured observations (EWMA, $\lambda = 0.1$)
(g) Control chart for the measured observations (EWMA, $\lambda = 0.2$)
(h) Control chart for the measured observations (Shewhart)

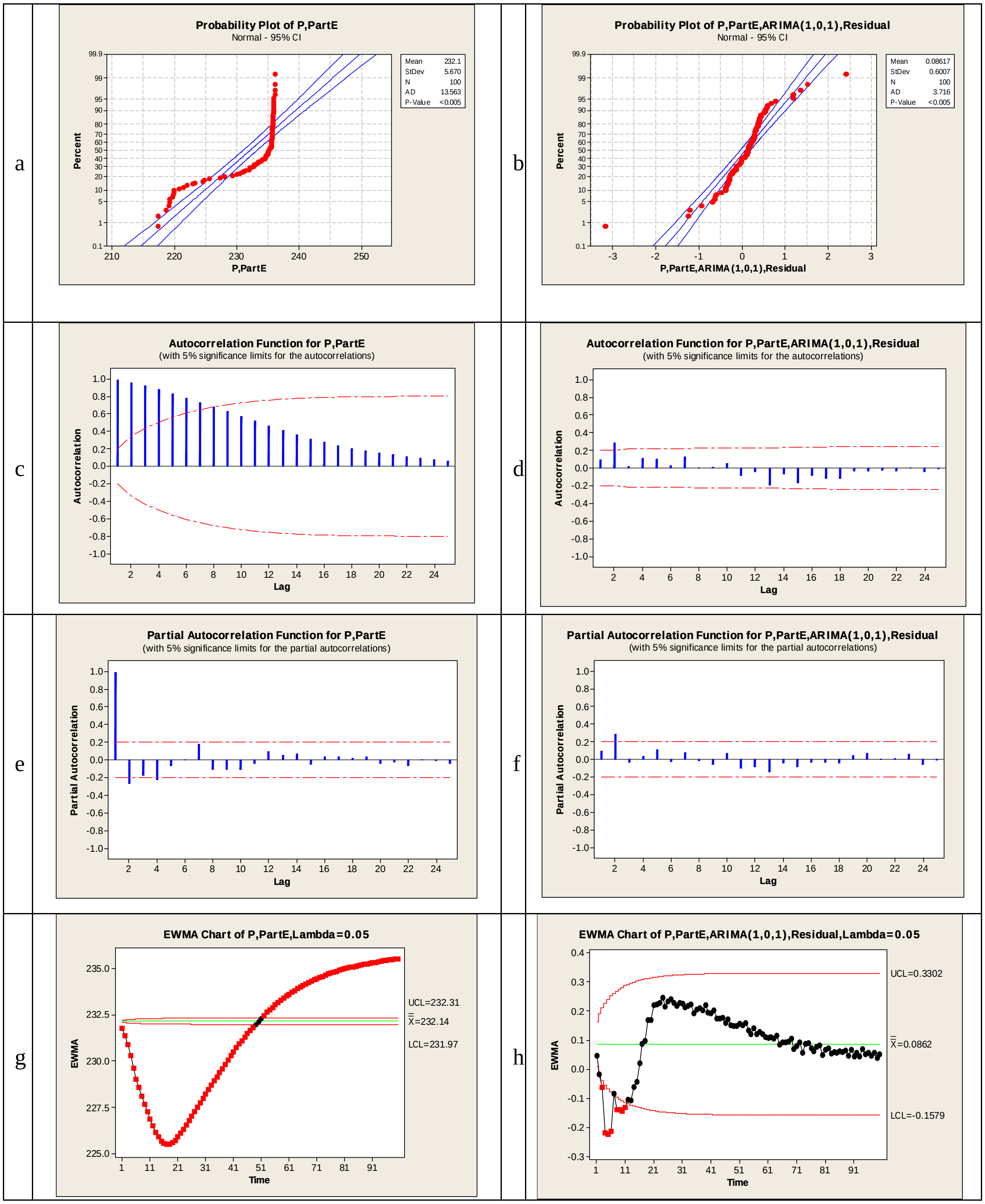

Fig. 9. Normality test, Autocorrelation test, and Control chart selection steps of the five-step procedure for process identification, monitoring, and control for the second approach, the fifth part

(a) Normality test on the measured observations (before model selection)
(b) Normality test on residuals (after model selection)
(c) Autocorrelation Test (ACF) on the measured observations (before model selection)
(d) Autocorrelation Test (ACF) on residuals (after model selection)
(e) Autocorrelation Test (PCF) on the measured observations (before model selection)
(f) Autocorrelation Test (PCF) on residuals (after model selection)
(g) Control chart for the measured observations (before model selection)
(h) Control chart for residuals (after model selection)

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