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Managed Pressure Drilling Using Integrated Process Control

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Abstract

Control of wellbore pressure during drilling operations has always been important in the oil industry as this can prevent the possibility of well blowout. The present research employs a combination of automatic process control and statistical process control for the first time for the identification, monitoring, and control of both random and special causes in drilling operations. To this end, by using automatic process control, control charts are applied to the output of the controlled process; subsequently, the points which are outside the predefined control limits are identified. This method is capable of using controllable input variables not used in automatic process control, such as changes in the mud weight, to fully control the process. Due to the dynamic nature of the process, adaptive model-based controllers have replaced feedback methods in automatic process control. Control charts have also been used to compare the performance of different automatic process control approaches. Based on this new criterion, the fuzzy adaptive approach is shown to have good performance in automatic process control. The results indicate that this approach can improve the limits of the automatic process control method by using statistical process control for controlling the bit pressure in an acceptable range.

Keywords: Automatic Process Control, Integrated Process Control, Managed Pressure Drilling, Statistical Process Control, Well Blowout.

1. Introduction

Automation and intelligent design of processes in oil and gas industry have always attracted the attention of experts interested in improving quality, efficiency, safety, environmental protection, yield, and profit. The drilling industry as one of the important and upstream oil industries is considered to be a high-risk operation. One of the possible risks in the drilling industry is the danger of oil well blowout. Blowout occurs after the unsuccessful control of the kick, leading to severe injuries, as well as financial and environmental damage. One of the most recent oil well blowouts happened in Rag-Sefid oil field in Iran in 2017, leading to two deaths and the injury of six other people. This oil well was finally controlled after 60 days.

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The intelligent design of the drilling operation can be an effective method to prevent well blowouts from occurring. Because of the importance of this issue, numerous studies have been published in this regard. Among the proposed methods, managed pressure drilling (MPD) has been employed to monitor and control the fluid pressure inside the bit during its operation. MPD uses common automatic process control (APC) approaches to predict well (drilling bit) pressure and control and change this pressure within an acceptable range (Kaasa et al., 2012).

Until now, several methods have been proposed by the researchers in this regard. Salahshoor and Lotfi (2013) used a self-tuning controller (STC) in order to keep the bit pressure at the set points. The results showed the superiority of the STC method over the PI controller based on the mean square error (MSE) and mean absolute error (MAE) criteria. Anfinsen et al. (2017) also utilized a model reference adaptive controller (MRAC) to control the bit pressure during the drilling operation. The results were then compared with those obtained by a PI controller, confirming the superiority of MRAC with fewer tracking errors and oscillations.

Based on the second law of thermodynamics, all processes tend toward increased entropy. This entropy affects the process output through random and special causes. APC methods such as adaptive controllers can control and compensate for random causes. Further, by employing statistical process control (SPC) methods such as control charts, the identification and elimination of special causes are conducted. It has been shown that control and compensation of special causes can result in dynamic changes in the process (Montgomery, 2009). This can be achieved by using APC instead of eliminating the causes by applying SPC. In oil well drilling, random causes include random deviations with sources hidden in the drilling operation. Special causes include deviations brought about by a source outside the drilling operation. An example of random causes is the kick phenomenon in the drilling operation, while reference tracking, mud loss, and damaged or faulty sensors are examples of special causes.

The results of studies carried out by Anfinsen et al. (2017) and Salahshoor and Lotfi (2013) for controlling the bit pressure using APC have shown that this approach can be very successful in controlling the random causes. However, severe variations are observed in the controller output during the presence of the special causes, indicating that the APC approach is not able to control both random and special causes simultaneously. Therefore, the use of the SPC approach along with APC is proposed in order to fully control the process. This approach is called the integrated process control (IPC). IPC is an approach using APC and SPC methods to complement each other and fully identify, monitor, compensate for, and control both random and special causes during operations (Box and Narasimhan, 2010).

The current study uses a suitable black box time series on the outputs of different APC methods and implements suitable control charts on the residual values. Using SPC and input parameters not controlled in the APC approach, we seek to fully control the process. Furthermore, control charts are used so as to compare different APC methods, and then the results are compared to those of other common performance evaluation methods in APC.

2. System description

The white box model of the process is necessary for the implementation of some APC methods. Therefore, a dynamic model of the drilling process along with inputs and outputs is presented along with a description of the drilling operation and well pressure control.

The drilling mud enters the well through the mud pump and the drill string; then, it is transported to the surface after going through the annulus and exiting through the choke valve.

The drilling mud cools down the bit and removes the resulting cuttings while also creating the necessary hydrostatic pressure in the well to prevent any kicks during the drilling operation. The highest hydrostatic pressure due to mud is at the lowest point of the well or the drilling bit. Therefore, controlling the bit pressure is the same as controlling the well. As a result, the drilling bit pressure is considered to be the output of the process. One of the parameters affecting the process with a short time delay is the exit choke valve of the well. As a result, the choke valve is used as the controllable input in the APC. Another parameter which has a long-time delay and is used in the SPC approach is the mud weight entering the well.

Table 1

Model variables and initial values of the main variables and constant parameters.

Variable / Parameter	Description	Value
P_p	Mud pump pressure (bar)	-
P_c	Choke manifold pressure (bar)	-
P_b	Bit pressure (bar)	-
q_p	Mud pump flow rate (m^3/s)	-
q_c	Choke manifold flow rate (m^3/s)	-
q_b	Bit flow rate (m^3/s)	-
p_p^0	Initial mud pump pressure (bar)	120
p_c^0	Initial choke manifold pressure (bar)	70
q_b^0	Initial bit flow rate (m^3/s)	0.014
β_a	Annulus mud bulk modulus (bar)	14000
β_d	Drill string mud bulk modulus (bar)	14000
V_a	Annulus volume (m^3)	96.1327
V_d	Drill string volume (m^3)	28.2743
M_a	Mass coefficient of the annulus (10^{-5} × kg/m^4)	1600
M_d	Mass coefficient of the drill string (10^{-5} × kg/m^4)	5720
F_a	Annulus friction factor	20800
F_d	Drill string friction factor	165000
ρ_a	Annulus density (10^{-5} × kg/m^3)	0.0119
ρ_d	Drill string density (10^{-5} × kg/m^3)	0.0125
h_b	Vertical depth of the drill bit (m)	2000
g	Gravity acceleration (m/s^2)	9.81
q_r	Flow rate of reservoir fluids (m^3/s)	0.001
q_{back}	Back pump flow rate (m^3/s)	0.003
P_0	Pressure outside system (bar)	1

The nonlinear model presented by Kaasa et al. (2012) is used here.

$$\dot{p}_p = a_1\left(q_p - q_b\right) \quad , \; a_1 = \frac{\beta_d}{V_d} \tag{1}$$

$$\dot{p}_c = a_2\left(q_b + q_r + q_{back} - q_c - \dot{V}_a\right) \quad , \; a_2 = \frac{\beta_a}{V_a} \tag{2}$$

$$\dot{q}_b = a_3\left(p_p - p_c\right) - a_4\left(q_b\right)^2 - a_5 q_b + a_3 q_r (q_b + q_r) + a_6 h_b \quad , a_3 = \frac{1}{\left[M_a + M_d\right]} \; , a_4 = \frac{F_d}{\left[M_a + M_d\right]} ,$$
$$a_5 = \frac{F_a}{\left[M_a + M_d\right]} , a_6 = \frac{\left(\bar{\rho}_d - \bar{\rho}_a\right)g}{\left[M_a + M_d\right]} \tag{3}$$

Based on the above equations, the bit pressure is calculated according to Equation 4.

$$p_b = p_c + M_a \dot{q}_b + F_a q_b + q_r (q_b + q_r) + \bar{\rho}_a g h \tag{4}$$

The model variables, their initial values, and model parameters related to this dynamic model are listed in Table 1.

3. Methodology

This section introduces novel APC methods for the identification, control, and compensation of random causes during the process. Afterward, various types and conditions of control charts used in SPC for the monitoring, identification, and elimination of the special causes in autocorrelated processes are explained. Finally, the IPC method is introduced as a way of simultaneously controlling both random and special causes in a process.

3.1. Automatic process control

Many industrial processes have dynamics and time-varying disturbances. In some of these processes, changes are due to various factors and resources that are not sometimes possible to identify or are not economically viable. Therefore, it is always important to select the appropriate controller to adapt to these changes of conditions, which occur with time. Adaptive controllers are used for this purpose. With a mechanism for adjusting the parameters, these controllers can effectively change their behavior to adapt to the dynamic changes in the process and disturbances. These controllers consist of two loops, including a typical feedback for the process and controller and another one for adjusting the parameters (Imanian et al., 2018b).

In the following section, three types of adaptable controllers used in APC are introduced.

a. Self-tuning controllers (STC)

Self-tuning controllers can be designed in both direct and indirect ways. In the direct method, the parameters of the controller are estimated directly. In the indirect method, however, the system parameters are first estimated, and then the controller parameters are calculated based on the estimated values (Salahshoor and Lotfi, 2013).

By considering a second-order, discrete, linear system, we can express the process model by Equation 5:

$$G = \frac{B}{A} = \frac{\left(b_0 + b_1 q^{-1}\right)q^{-1}}{1 + a_1 q^{-1} + a_2 q^{-2}} \tag{5}$$

where a_0, a_1, b_0, and b_1 are the unknown parameters of the system. Due to the nonlinearity of the system and the time-variable parameters, the recursive least squares (RLS) algorithm is used for the online estimation of these parameters; then, the estimated values are sent to the control system. Equation 6 deals with the equations used for estimating the system parameters based on this algorithm:

$$\begin{aligned} &\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)\left[y(t) - \phi^T(t)\hat{\theta}(t-1)\right] \quad , \quad K(t) = P(t-1)\phi(t)\left[I + \phi^T(t)P(t-1)\phi(t)\right]^{-1} \quad , \\ &P(t) = \left[I - K(t)\phi^T(t)\right]P(t-1) \quad , \quad \hat{\theta} = \left[b_0 \quad b_1 \quad a_1 \quad a_2\right]^T \end{aligned} \tag{6}$$

Also, the control laws for this controller are based on Equation 7:

$$u = \frac{T}{R}u_c - \frac{S}{R}y \quad , \quad R = q + r_1 \quad , \quad T = t_0 q + t_1 \quad , \quad S = s_0 q + s_1 \quad , \quad A_0 = q \tag{7}$$

where u_c *is* the value of the set point, u is the process controllable input, and y represents the process output.

b. Model-reference adaptive controllers (MRAC)

Model-reference adaptive controllers can be considered as a servo-adaptive controller in which the optimal performance is achieved via the optimal response of the reference model to the signal u_c. In this controller, it is assumed that the structure of the process is known, and its parameters are uncertain. This means that the number of poles and zeros of the system is clear, but their location is unknown. In nonlinear processes, the structure of the dynamic equations is known, but some of its parameters are unknown (Astrom and Wittenmark, 2008).

Given a first-order system, the process model can be represented as follows:

$$\dot{y} = \theta\left(\delta(t) - u(t)\right) \tag{8}$$

In order to design the MRAC, a reliable reference model is required. For the first-order system, Equation 9 is considered:

$$\dot{y}_m = a_m p_m + b_m r \tag{9}$$

By considering the tracking error $e = y - y_m$ and defining the definitely positive Equation 10, the appropriate control laws for this controller can be obtained according to Equation 11.

$$V = a_m^2 e^2 + \frac{1}{\gamma_0}\left(\theta k_0 - b_m\right)^2 + \frac{1}{\gamma_1}\left(-\theta k_1 - a_m\right)^2 + \frac{1}{\gamma_2}\left(\theta\delta - \theta k_2\right)^2 \tag{10}$$

$$u = -k_0 r + k_1 y + k_2 \quad , \quad \dot{k}_0 = -\frac{\gamma_0}{\theta}a_m^2 er \quad , \quad \dot{k}_1 = -\frac{\gamma_1}{\theta}a_m^2 ey \quad , \quad \dot{k}_2 = \frac{\gamma_2}{\theta}a_m^2 e \tag{11}$$

where r is the reference input for tracking, y is the output of the system, γ_1, γ_2, and $\gamma_3 > 0$ are strictly positive constants, and k_1, k_2, and k_3 are variable gains with time for maintaining the Lyapunov stability of the system.

c. Fuzzy adaptive controllers

In fuzzy adaptive controllers, by using the fuzzy logic instead of changing the parameters of the controller, the control signal changes in order to obtain the desired output. In this controller, from the beginning, fuzzy systems are built on control knowledge (Imanian et al., 2019).

For the direct fuzzy adaptive controllers, the mathematical model of the system is based on Equation 12:

$$y^{(n)} = f(y) + g(y)u \tag{12}$$

where y is the n-dimensional vector of the system state, g is an indefinite positive constant function, and f is considered to be an unknown function. Both functions f and g are nonlinear. Here u is a process controllable input.

The system tracking error is calculated based on equation $e = y_d - y$, where y_d is the desired output. The optimal control law is defined by the following equation:

$$u^* = g^{-1}\left(y_d^{(n)} - f + k^T e\right) \tag{13}$$

where k is a positive constant. This constant is used to maintain the dynamic stability of the closed loop system error and ensure that the error is converted to zero through the relationship $e^{(n)} + k^T e = 0$.

Given the uncertainty of nonlinear functions f and g, we can use the characteristics of the fuzzy system in approximating these functions to achieve the control signal u^* with the desired accuracy. As a result, the new control law is proposed as follows:

$$u^* = \hat{u}(e, \theta) \tag{14}$$

where û is a fuzzy system used to approximate the control law u^*. For this purpose, the zero-order fuzzy, single-input Takagi-Sugeno system is applied according to the following equation:

$$R^{(l)} : if\ \ e\ \text{ is } A^l \text{ , then } \hat{u}\ is\ C^l,\ l = 1, 2, ..., m \tag{15}$$

where e and û are the input and output of the fuzzy system respectively. A^1 and C^1 represent fuzzy inputs and outputs respectively.

By using a singleton fuzzy and a multiplication inference engine, the fuzzy system is given by:

$$\hat{u} = \frac{\sum_{l=1}^{M} C^l \mu_{A^l}(e)}{\sum_{l=1}^{M} \mu_{A^l}(e)} \tag{16}$$

where $\mu_{A^l}(e)$ is the input membership function.

The base fuzzy function is defined according to the following equation:

$$\psi_l = \frac{\mu_{A^l}(e)}{\sum_{l=1}^{M} \mu_{A^l}(e)} \tag{17}$$

By considering $\psi(e)=\left[\psi_1(e),\psi_2(e),...,\psi_M(e)\right]^T \;\; \mu_{A'}(e)$ and $\theta^T=\left[C^1,C^2,...,C^M\right]=\left[\theta_1,\theta_2,...,\theta_M\right]$, we can write the fuzzy system of Equation 16 according to the following equation:

$$\hat{u}=\theta^T\psi(e) \tag{18}$$

The nonlinear function estimated by the fuzzy system $u^*(e)$ can be written as follows:

$$u^*(e)=\hat{u}(e,\theta^*)+\delta(e)=\theta^{*T}\psi(e)+\delta(e) \tag{19}$$

where $\delta(e)$ is the minimum error of the approximation of the fuzzy system and θ^* is the vector of the optimal parameters, which is calculated according to equation $\theta^*=\arg\min_\theta\left[\sup_{e\in R}\left|\hat{u}\left(e,\theta\right)-u^*(e)\right|\right]$.

Considering a one-dimensional system, Equation 12 for a first-order mathematical model is converted as follows:

$$\dot{y}=f+gu \tag{20}$$

The desired optimal control law is expressed through Equation 13:

$$u^*=\hat{g}^{-1}\left(\dot{y}_d-\hat{f}-k^Te\right) \tag{21}$$

$\hat{f}$ and $\hat{g}$ are the approximation of nonlinear functions *f* and *g*, which can be obtained later through adaptive laws.

Nonlinear functions *f* and *g* are approximated by utilizing the following two fuzzy systems:

$$\hat{f}(e)=W_f^T\xi_f(e) \tag{22}$$

$$\hat{g}(e)=W_g^T\xi_g(e) \tag{23}$$

Where vectors W_f^T and W_g^T are unknown values in the "then-part" of the fuzzy rules. It is assumed that functions *f* and *g* are equivalent to the fuzzy system, and their then-part is unspecified. As a result, nonlinear functions *f* and *g* are based on the optimal vectors according to the following equations:

$$f(e)=W_f^{*T}\xi_f(e) \tag{24}$$

$$g(e)=W_g^{*T}\xi_g(e) \tag{25}$$

Where vectors W_f^{*T} and W_g^{*T} are the optimal parameters with unknown values in the then-part of the fuzzy rules. Here, the goal is the convergence of W_f^T and W_g^T to their optimal values W_f^{*T} and W_g^{*T}. For this purpose, the dynamics of the loop system error are obtained from the following equation:

$$\dot{e}=f-\hat{f}+\left(g-\hat{g}\right)u-ke \tag{26}$$

By substituting Equations 22, 23, 24, and 25 in Equation 26, the following equation is obtained:

$$e = \left(W_f^T - W_f^{*T}\right)\xi_f(e) + \left(W_g^T - W_g^{*T}\right)\xi_g(e)u - ke \tag{27}$$

The following definitely positive function is proposed as the candidate Lyapunov function:

$$V = \frac{1}{2}e^2 + \frac{1}{2\gamma_f}\tilde{W}_f^T\tilde{W}_f + \frac{1}{2\gamma_g}\tilde{W}_g^T\tilde{W}_g \tag{28}$$

where γ_g and γ_f are the strictly positive constants and $\tilde{W}_f = W_f^T - W_f^{*T}$ and $\tilde{W}_g = W_g^T - W_g^{*T}$ are also taken into account.

By taking the derivative of V and simplifying it, the following equation is obtained:

$$\dot{V} = -ke^2 + \tilde{W}_f^T\left(e\tilde{W}_f^T\xi_f(e) + \frac{1}{\gamma_f\dot{\tilde{W}}_f^T}\right) + \tilde{W}_g^T\left(e\tilde{W}_g^T\xi_g(e)u + \frac{1}{\gamma_g}\dot{\tilde{W}}_g^T\right) \tag{29}$$

By considering the following adaptive laws, the stability of the system can be guaranteed on the basis of a Lyapunov function $(\dot{V} \le 0)$:

$$\dot{\tilde{W}}_f^T = -\gamma_f e\tilde{W}_f^T\xi_f(e) \tag{30}$$

$$\dot{\tilde{W}}_g^T = -\gamma_g e\tilde{W}_g^T\xi_g(e)u \tag{31}$$

In fact, the two adaptive rules outlined above represent the then-part of fuzzy rules that are obtained over time.

In the simulation for the approximation of *f* and *g*, two fuzzy systems are used, each of which has five laws. The then-part of these rules is based on the adaptive laws mentioned above. For each input, five membership functions are taken into account. The set of centers of the membership functions is equal to $[-1 \quad -0.5 \quad 0 \quad 0.5 \quad 1]$. The functions are Gaussian, and the standard deviation of each of these Gaussian functions is 0.25.

d. Performance evaluation

There are several methods to evaluate the performance of APC. Among these, the response step criterion should be noted. In this criterion, a step change in the input signal disrupts a stable process, and then the process outputs are observed. APC methods are evaluated based on the following factors: overshoot, steady state error, dead time, rise time, and settling time.

One of the methods used for evaluating the performance of controllers is the use of cost functions. In addition, cost functions are also used to optimize the controller coefficients. Subsequently, some of these functions have been presented.

- Integral absolute error (IAE)
- Integral time absolute error (ITAE)
- Integral square error (ISE)
- Integral time square error (ITSE)

Alongside the abovementioned methods, control charts can also be used to evaluate the performance of the outputs produced by APC methods. By investigating the number of out-of-control points during the process, it is possible to compare the performance of different APC methods within the process control. APC methods with the lowest number of out-of-control points have better performance, as compared to other methods.

3.2. Statistical process control

Control charts can be considered as one of the most important tools in SPC. They are employed to monitor and control discrete processes with normal and independent data (Montgomery, 2009). The application of the novel five-step approach, as will be described later, makes it possible to exploit this method to monitor and control abnormal, autocorrelated, and continuous processes (Imanian et al., 2018a).

Observation and data gathering can be regarded as the first step in this five-step approach. Sampling time (ST) is one of the most important parameters considered in this step. A decrease in ST can enhance autocorrelation between observations, thereby changing the process from a discrete one to a continuous one (del Castillo, 2002).

It is known that a requirement in the application of control charts is the normality of the observations. This can be tested by using histograms and the Anderson-Darling normality test. These tests are commonly conducted by employing statistical software applications such as SPSS at various confidence intervals.

Another condition that has to be met in order to make it possible to use control charts is ensuring the lack of autocorrelation between observations. It is possible to consider the correlation between the observations in different lags by drawing the autocorrelation function (ACF) and partial autocorrelation function (PCF) charts. If the values given for each lag violate the set limits, it means that there are autocorrelation and partial autocorrelation in that lag.

Autocorrelation between observations can be removed by means of model-based methods. A time series model is fitted to the observations in these methods, according to the Box-Jenkins approach (Box et al., 2015). Subsequently, the residual values which lie between the actual values (x_t) and the fitted time series model ($\hat{x}_t$) are calculated. It should be noted that these residual values lack any significant autocorrelation.

The general format of the time series model auto regressive integrated moving average (ARIMA) (*p*, *d*, *q*) can be seen in Equation 32:

$$\Phi_p(B).\nabla^d.x_t = \Theta_q(B).\varepsilon_t \tag{32}$$

where

$\Phi_p(B) = \left(1-\varphi_1 B - \varphi_2 B^2 - ... - \varphi_p B^p\right)$ refers to the autoregressive polynomial of the $p-th$ order, $\Theta_q(B) = \left(1-\theta_1 B - \theta_2 B^2 - ... - \theta_q B^q\right)$ indicates the moving averages polynomial of the $q-th$ order, ∇ stands for the backward, *d* is the difference order, *t* represents time, *B* is the back shift operator $B.x_t = (x_{t-1})$, $\varphi_1, \varphi_2, ..., \varphi_p$ represent the parameters of the autoregressive model, $\theta_1, \theta_2, ..., \theta_q$ stand for the parameters of the moving averages model, and ε_t indicates white noise.

The Augmented Dickey Fuller (ADF) test is used to determine the orders of *p* and *q*. This is based on the null hypothesis assuming the existence of a unit root and Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and Hannan-Quinn information criterion (HQC). A table was created for *p* and *q* values in the present research and filled by employing SBIC, AIC, and HQC criteria. Subsequently, by using the lowest value in that table, the suitable model was determined.

The use of ACF and PCF is another method that can be employed to determine the time series model *i*. According to this method, based on the number of lags that exceed the control limits of the PCF graph, the *p*-order is determined; then, the *q* order is determined according to the number of lags which exceed the control limits of the ACF chart (Gujarati and Porter, 2009).

The selection of the control chart is conducted according to certain criteria, including the normality of the observations, the autocorrelation level in the observations, the types of causes present, and the sampling time.

Control charts are divided into two groups: control charts with memory and those without memory. The latter simply employs current data points for process monitoring; Shewhart charts can be regarded as the most prominent example of this group. The former employs both current and past data points of the process for monitoring. EWMA and CUSUM charts are the most important examples in this group.

Control charts for process monitoring were first proposed by Shewhart (1931). These charts have shown a good performance in the monitoring and control of special causes; however, they lack the sensitivity required for identifying random causes (Montgomery, 2009). As a result of this shortcoming, CUSUM charts were developed by Page (1954), and EWMA charts were suggested by Roberts (1959) to monitor random causes. Owing to its simplicity, the present research employed EWMA charts to monitor random and special causes. Statistics and control limits of EWMA control charts can be seen in Equations 33 and 34 respectively.

$$Z_i = \lambda x_i + (1-\lambda) Z_{i-1} \tag{33}$$

$$\mu_0 \pm L\sigma \sqrt{\frac{\lambda}{2-\lambda}\left[1-(1-\lambda)^{2i}\right]} \tag{34}$$

where μ_0 is the target mean, σ represents the standard deviation, L is the width control limit factor, λ ($0 \leq \lambda \leq 1$) indicates the smoothing parameter, and Z_i stands for the EWMA statistics.

It has been pointed out by Montgomery (2009) that regarding abnormal observations, EWMA control charts with low λ values such as 0.05 or 0.1 can be used, yielding acceptable results.

It has also been demonstrated by Montgomery (2009) that in autocorrelation between observations, EWMA control charts with high values of λ could be more appropriate for achieving acceptable results with a low possibility of observation error.

3.3. Integrated process control

The integration of SPC and APC was first mentioned in 1988, when Box, Kramer, and MacGregor proposed this concept of integration. They managed to prove to the SPC research community that control charts could be used to monitor a "controlled" system. They reviewed the two schemes, their similarities, overlaps, contradictions, reasons behind their isolation, and the need for their integration. Montgomery (2009) also formulated a model for the integration of Shewhart and CUSUM control charts as monitoring tools and added the minimum mean squared error (MMSE) APC rule in their further work. Therefore, they were among the pioneers in the development of this integration technique.

According to various studies carried out by researchers, IPC can be used for any one of the following purposes:

- Integrating to reduce the causes of variation;
- Integrating to reject the resulting disturbances;
- Applying APC for controlling and SPC for monitoring;
- Integrating by using control actions;
- Integrating to minimize the quality deviation;
- Integrating to minimize the existing processes;

IPC methods are usually carried out in one of the following two ways. In the first approach, APC acts at the times when SPC is out of control and attempts to compensate for the changes and brings the process under control; this approach prevents unnecessary compensations. In the second approach, which is usually used for continuous high-risk operations, the process is simultaneously monitored by both the APC and the SPC methods.

The approach used in this study is similar to the second method. In this approach, the process is first controlled and compensated using the APC method; then, the process controlled by the APC is monitored using the SPC approach so as to identify and eliminate out-of-control points. This approach can identify, control, and eliminate both random and special causes.

4. Results and discussion

In this section, the proposed IPC approach was used for process control in MPD. To this end, the outputs of adaptive STR, MRAC, and fuzzy controllers implemented on the white box model of the process were monitored using control charts.

Table 2

Controller constants.

Parameters	**Controller**
$a_1 = -1.8$, $a_2 = 0.82$	STR
$a_m = b_m = 0.8$, $\gamma_0 = -0.5$, $\gamma_1 = 1.5$, $\gamma_2 = 0.9$	MRAC
$\gamma_f = 0.4$, $\gamma_g = 2\times10^{-5}$	Fuzzy

A summary of the control constants necessary for implementing the controllers of the previous section is presented in Table 2.

Figure 1 shows the output of controllers used in the MPD process. This figure uses the “reference tracking” scenario for creating the special causes. This scenario was defined based on the changes in set point pressures in different structures during the drilling operation. According to this figure, in times outside reference tracking, random causes could be successfully identified and compensated by the APC method. However, during the occurrence of special causes, significant variations could be seen in the output of all the three APC methods. In order to implement the APC and control bit pressure, the well’s output choke valve was used as the controllable input with a short time delay. Another controllable parameter which could affect the process output referred to the changes in the mud weight, which could not be used in the APC due to its long time delay. However, this input could be used in the SPC process control. The implementation of the SPC would require the selection and implementation of proper control charts. Therefore, a five-step approach was used. The first step was the gathering of necessary observations which, in this case, included the outputs of the APC-controlled process. These observations, which had an ST of 1 second, were recorded for 200 seconds. The second step was the investigation of the normality of the observations, as shown in Figure 2. Based on the Anderson-Darling test at the confidence interval of 95%, the outputs of all the three adaptive APC processes (real data) were abnormal. The third step consisted of the investigation of the autocorrelation of the process. According to Figure 3, the PCF and ACF graphs of all the three APC-controlled processes (real data) indicated autocorrelation between the observations. In order to remove this autocorrelation, in the fourth step, a suitable time series or black box was fitted on the outputs of all the three APC methods. Then, ADF and Phillips-Perron (PP), AIC, SBIC, and HQC measures were employed to investigate the unit root of the observations. According to the data presented in Table 3, after one step of differentiation, all the three nonstationary processes were changed into stationary processes. In this table, the degree of probability under 0.05 indicates a stationary process and lack of unit root. Based on these results, *d* was determined to be equal to one for all the three APC-controlled processes.

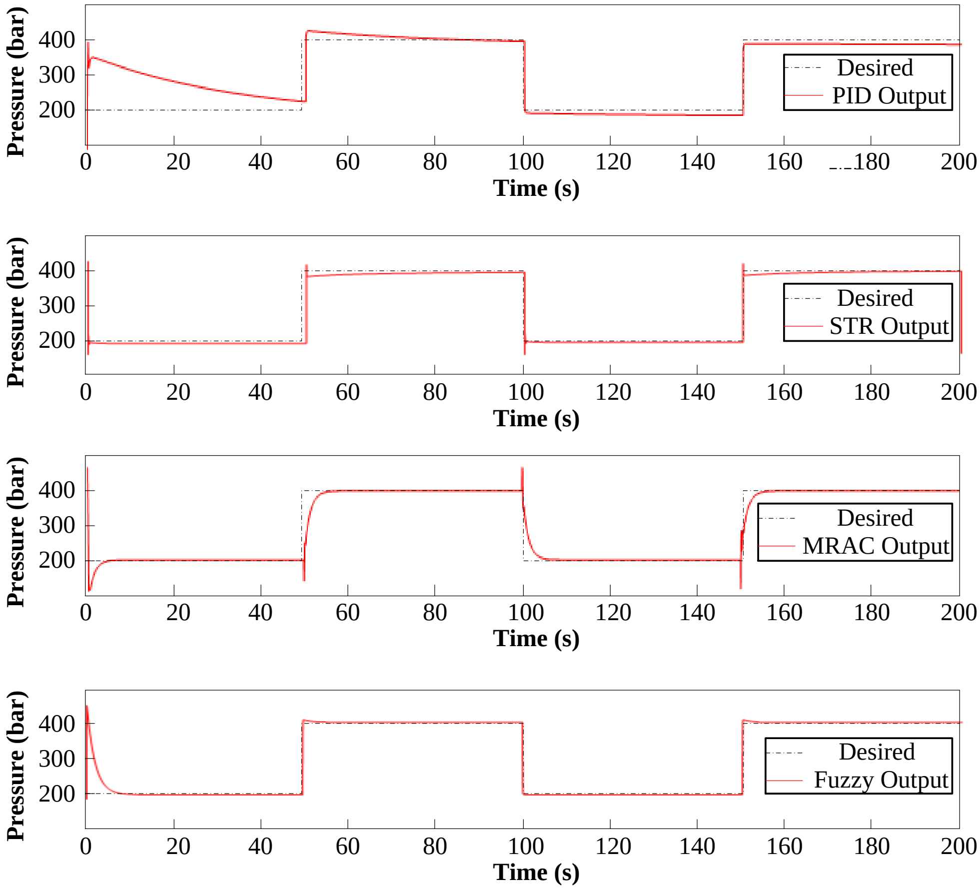


Figure 1

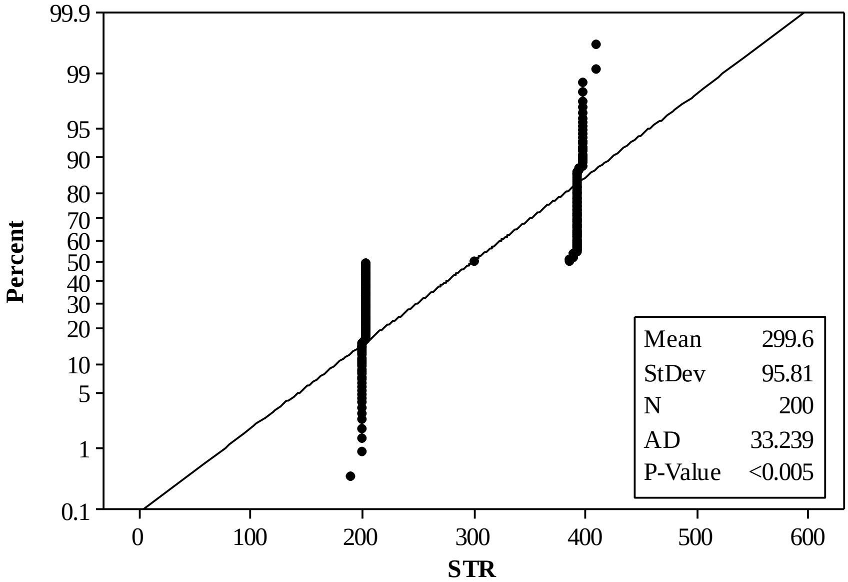
APC, the performance of output tracking by controllers, PID, STR, MRAC, and fuzzy adaptive.

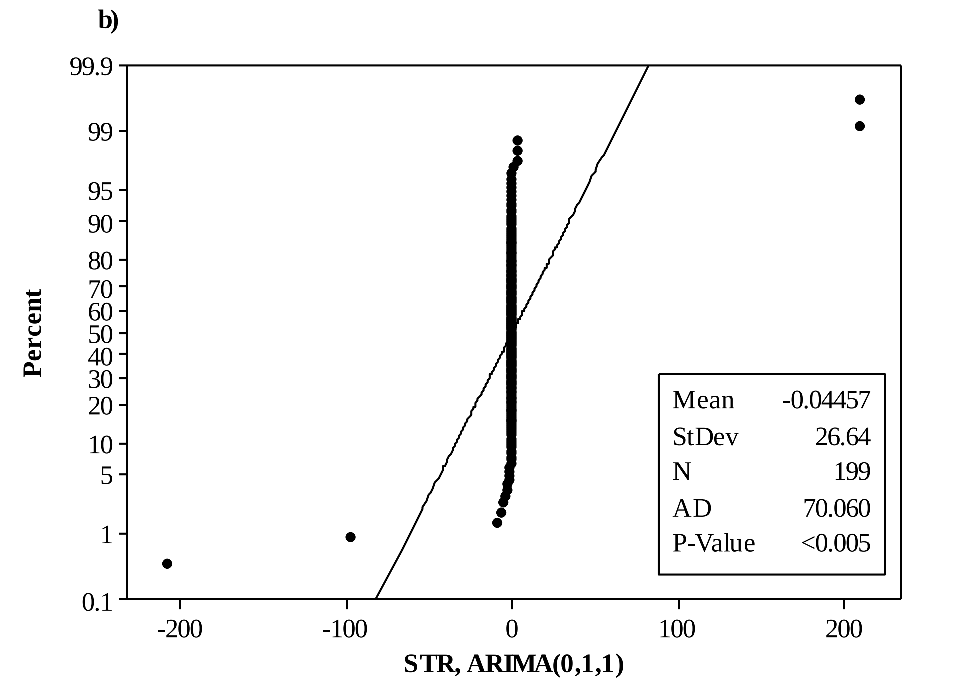
Table 3

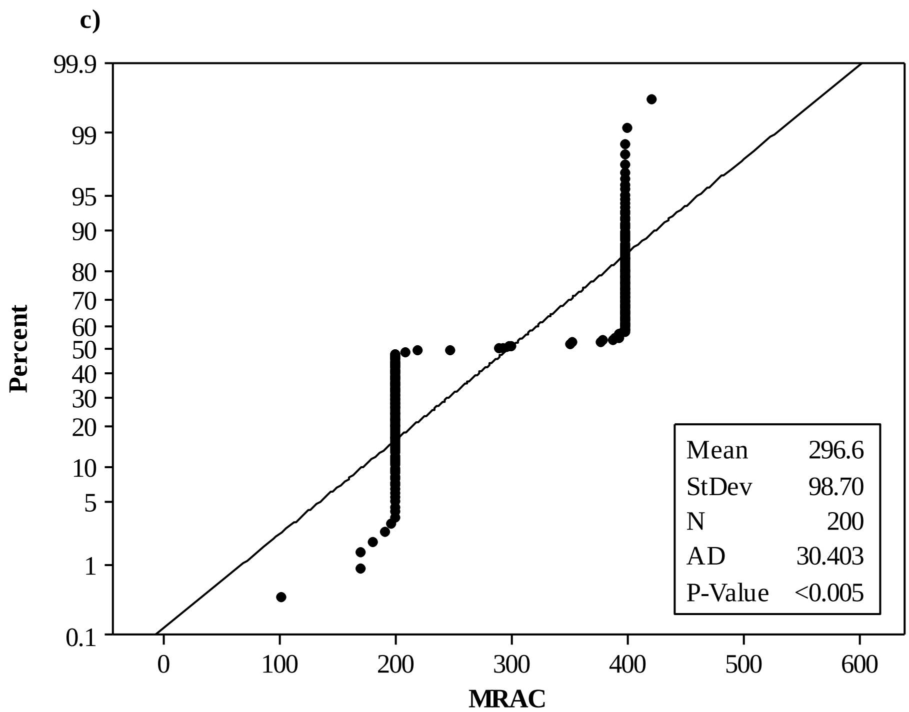
Unit root tests.

Unit root test / BHP and EPC method	Null hypothesis: BHP has a unit root (nonstationary) / 95% confidence level							
	ADF						PP	
	SIBC		AIC		HQ			
	t-Statistic	Prob	t-Statistic	Prob	t-Statistic	Prob	t-Statistic	Prob
BHP, STR	–1.852401	0.3544	–1.852401	0.3544	–1.852401	0.3544	–1.780932	0.3892
D(BHP), STR	–15.72275	0.0000	–15.72275	0.0000	–15.72275	0.0000	–15.72275	0.0000
BHP, MRAC	–1.830488	0.3649	–1.737656	0.4107	–1.830488	0.3649	–1.606336	0.4775
D(BHP), MRAC	–7.423543	0.0000	–6.028660	0.0000	–7.423543	0.0000	–15.48133	0.0000
BHP, Fuzzy	–2.457557	0.1276	–1.584501	0.4886	–1.584501	0.4886	–1.573516	0.4943
D(BHP), Fuzzy	–10.85154	0.0000	–10.85154	0.0000	–10.85154	0.0000	–12.09387	0.0000

a)




b)
99.9
99
95
90
80
70
60
50
40
30
20
10
5
1
0.1
Percent
-200
-100
0
100
200
STR, ARIMA(0,1,1)
Mean -0.04457
StDev 26.64
N 199
AD 70.060
P-Value <0.005


c)
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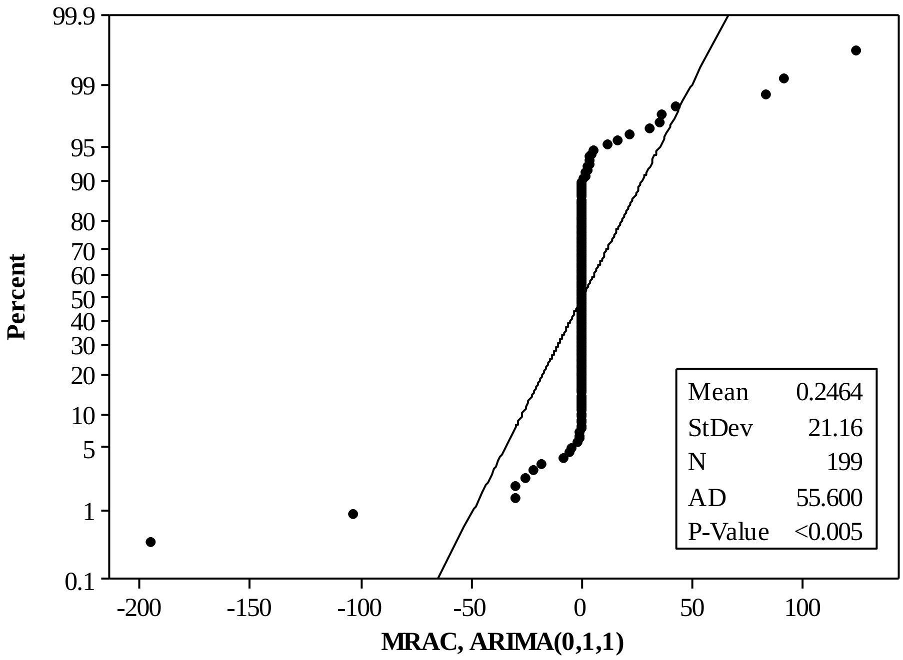
99
95
90
80
70
60
50
40
30
20
10
5
1
0.1
Percent
0
100
200
300
400
500
600
MRAC
Mean 296.6
StDev 98.70
N 200
AD 30.403
P-Value <0.005

d)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90
80
70
60
50
40
30
20
10
5
1
0.1
Percent
Mean 0.2464
StDev 21.16
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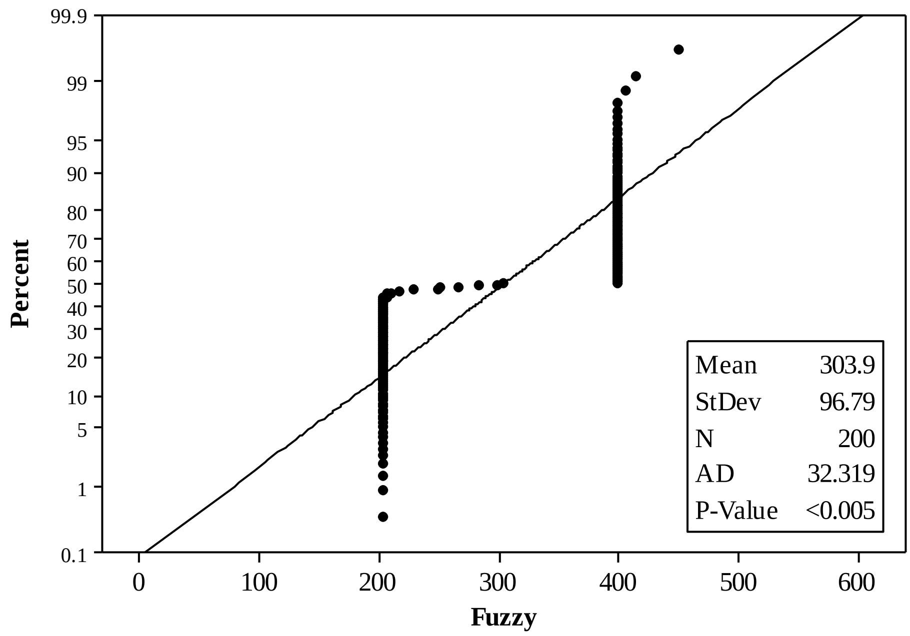
AD 55.600
P-Value <0.005
-200 -150 -100 -50 0 50 100
MRAC, ARIMA(0,1,1)

e)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60
50
40
30
20
10
5
1
0.1
Percent
Mean 303.9
StDev 96.79
N 200
AD 32.319
P-Value <0.005
0 100 200 300 400 500 600
Fuzzy

f)

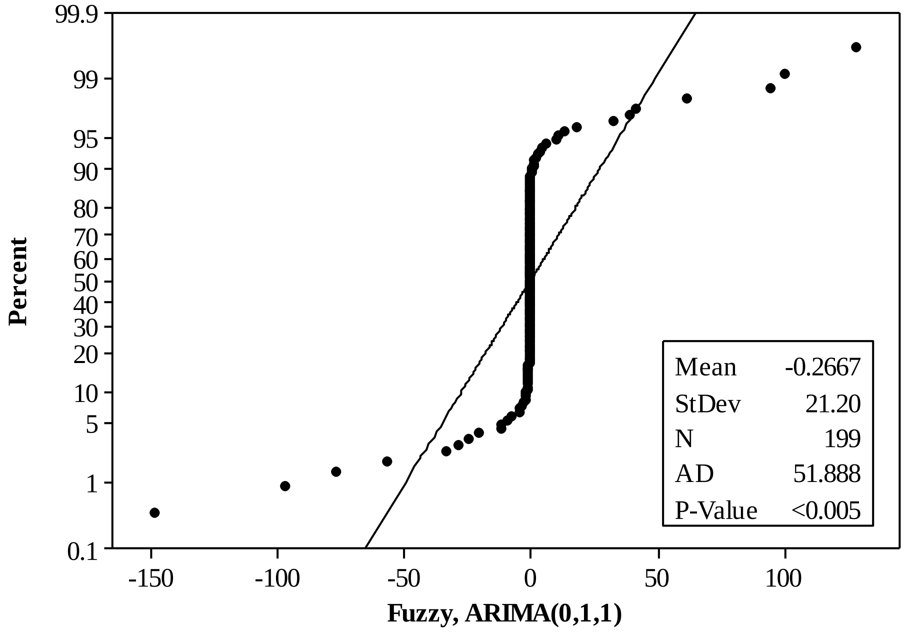
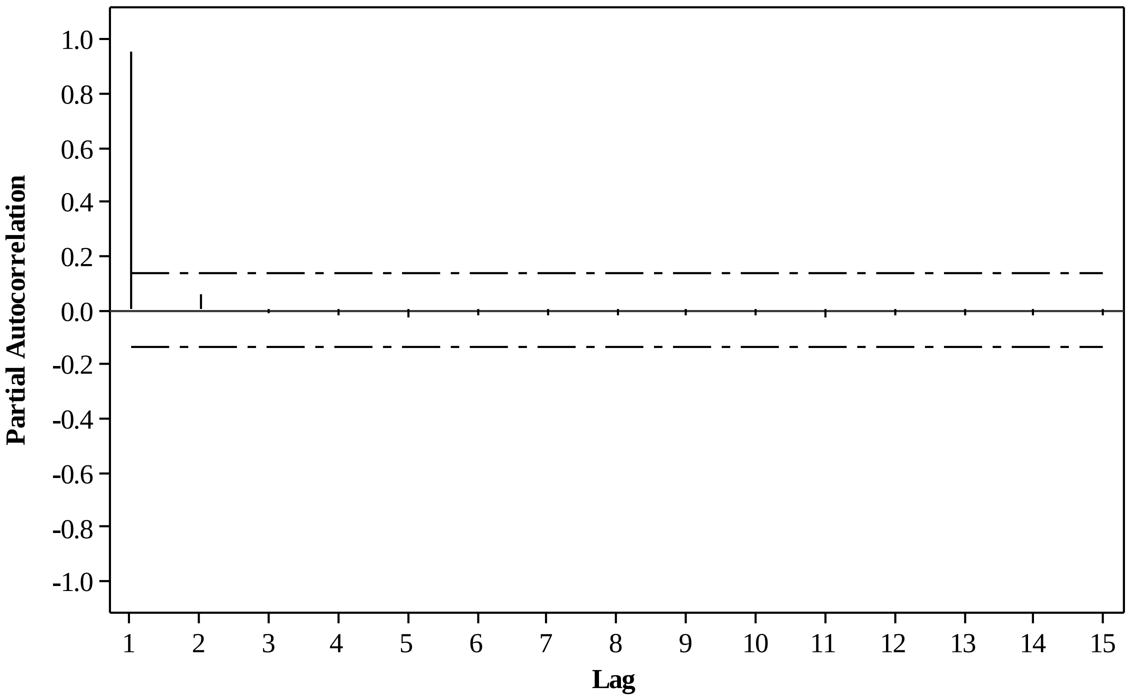


Figure 2

Normality test, real data, and residuals: a) probability plot of STR and real data; b) probability plot of STR, residual, ARIMA (0,1,1); c) probability plot of MRAC and real data; d) probability plot of MRAC, residual, and ARIMA (0,1,1); e) probability plot of fuzzy, real data; f) probability plot of fuzzy, residual, and ARIMA (0,1,1).

a)



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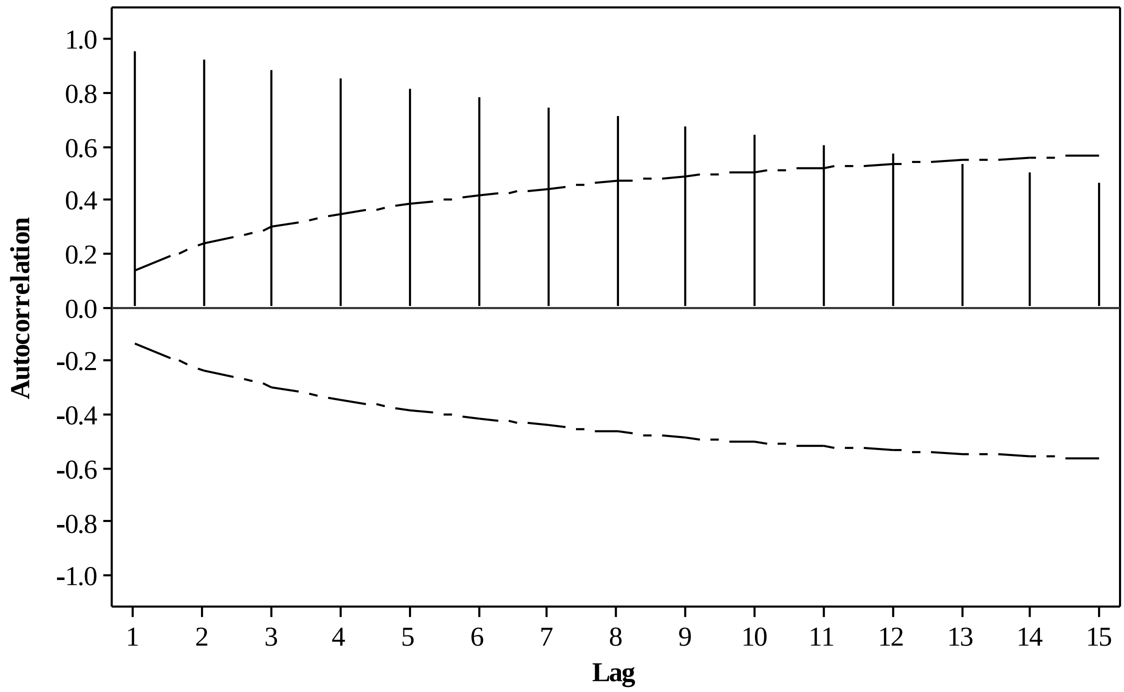
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0.4
0.2
0.0
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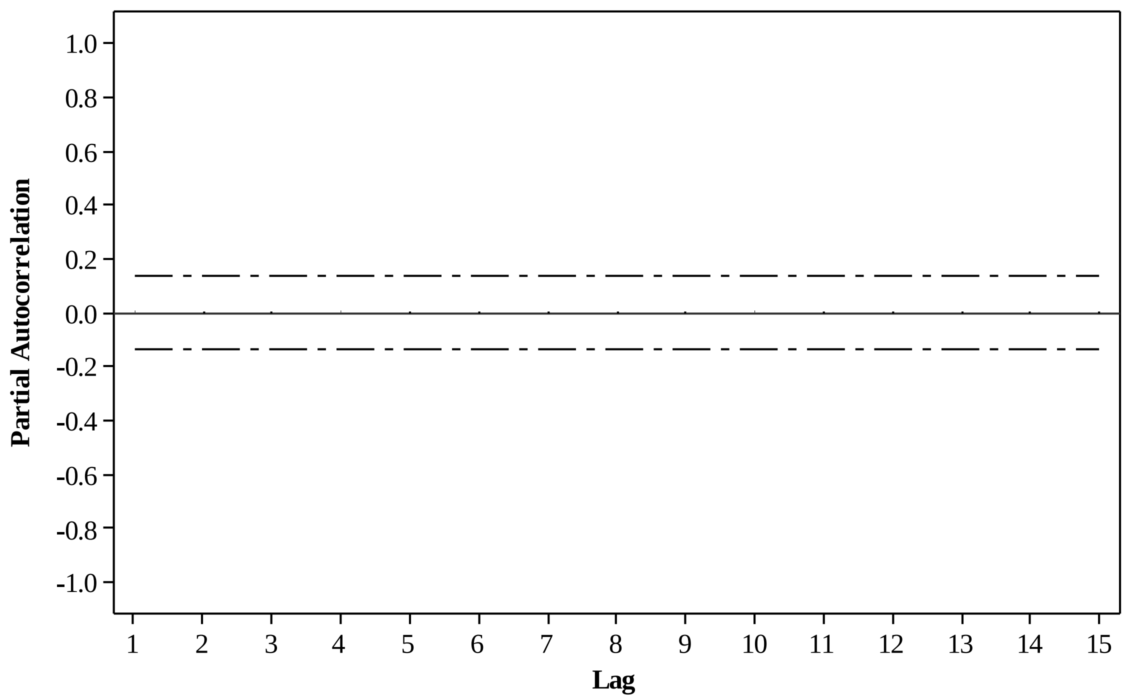
-0.4
-0.6
-0.8
-1.0
Autocorrelation
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Lag

c)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0.4
0.2
0.0
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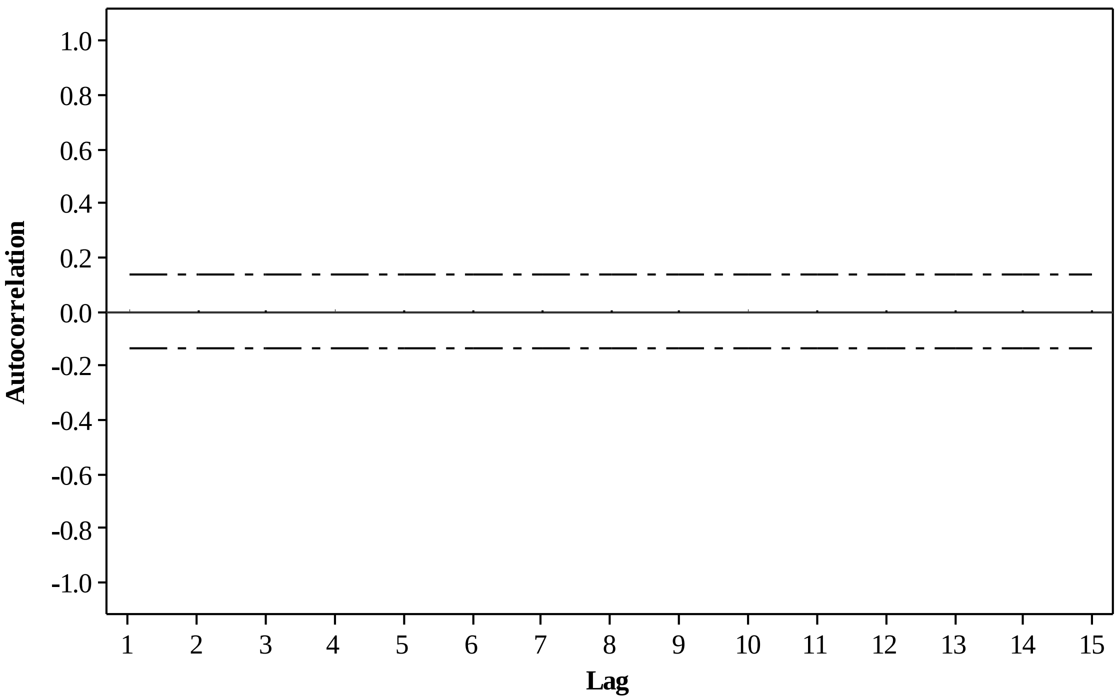
-1.0
Partial Autocorrelation
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Lag

d)


Autocorrelation
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0.6
0.4
0.2
0.0
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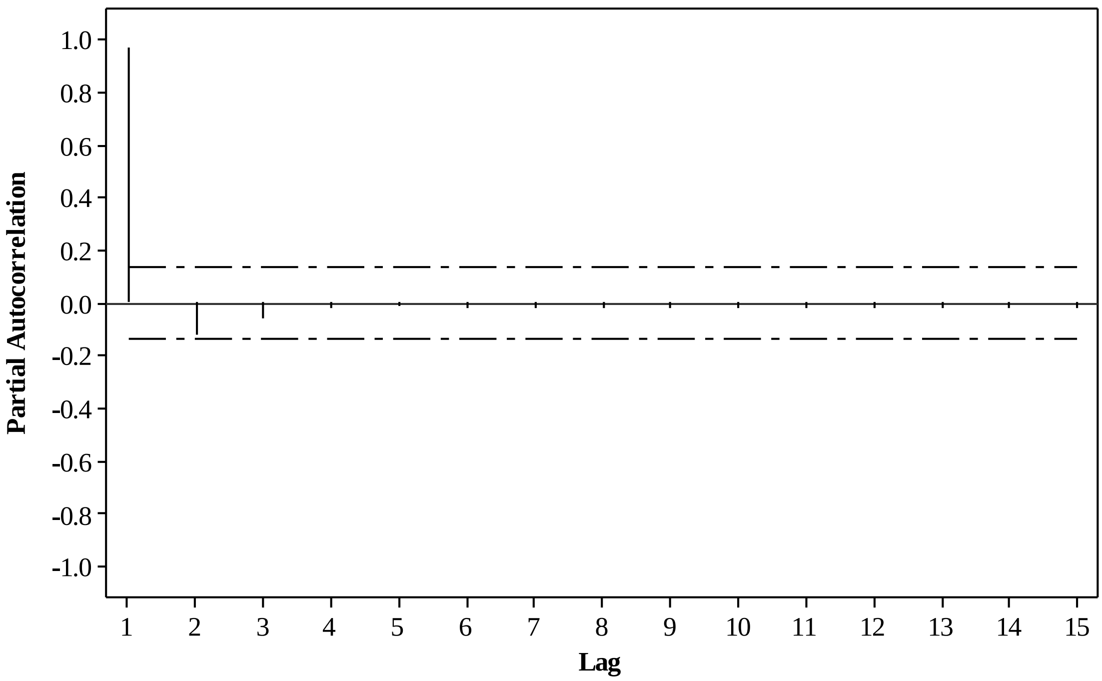
-0.4
-0.6
-0.8
-1.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Lag

e)


Partial Autocorrelation
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0.4
0.2
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-0.4
-0.6
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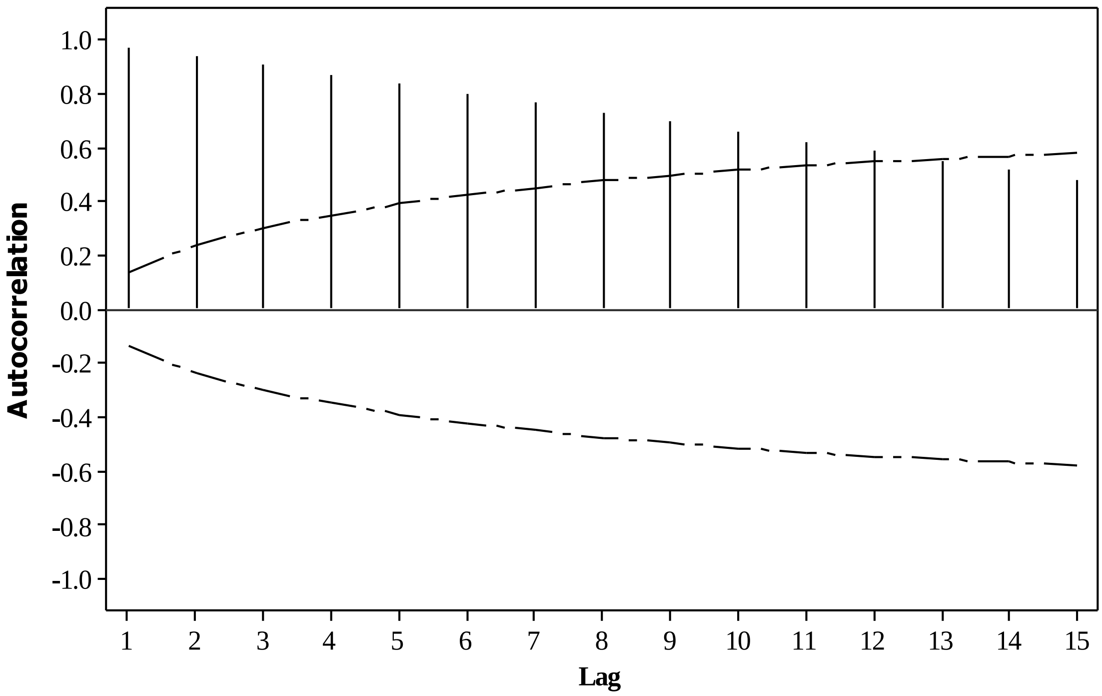
-1.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Lag

f)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0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
Autocorrelation
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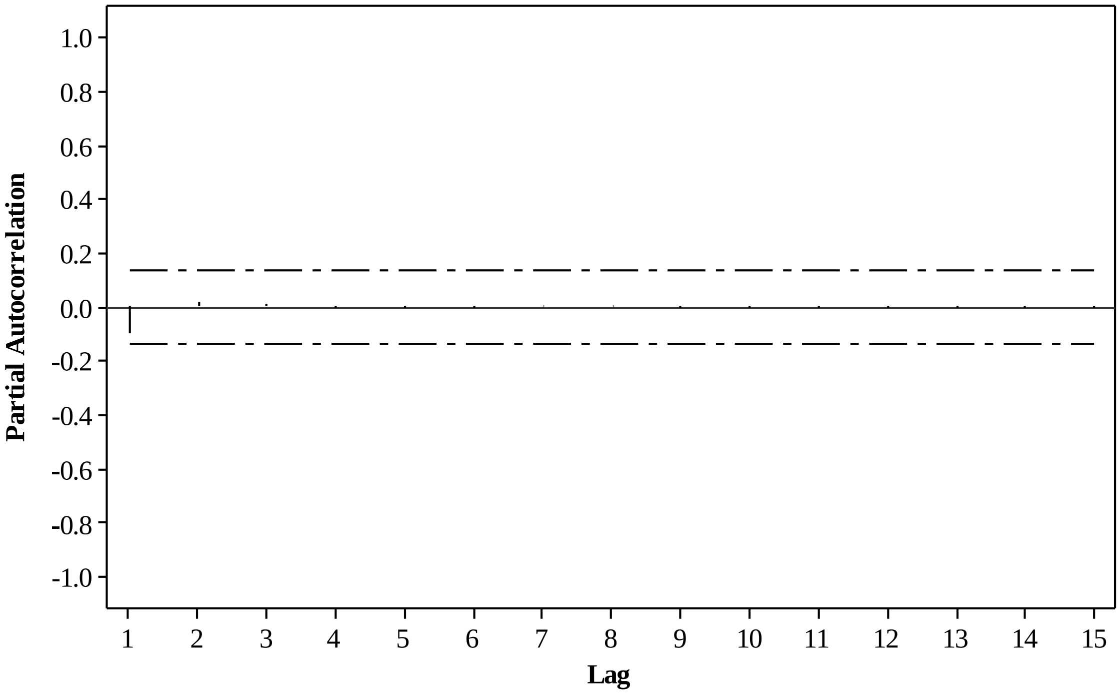
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Lag

g)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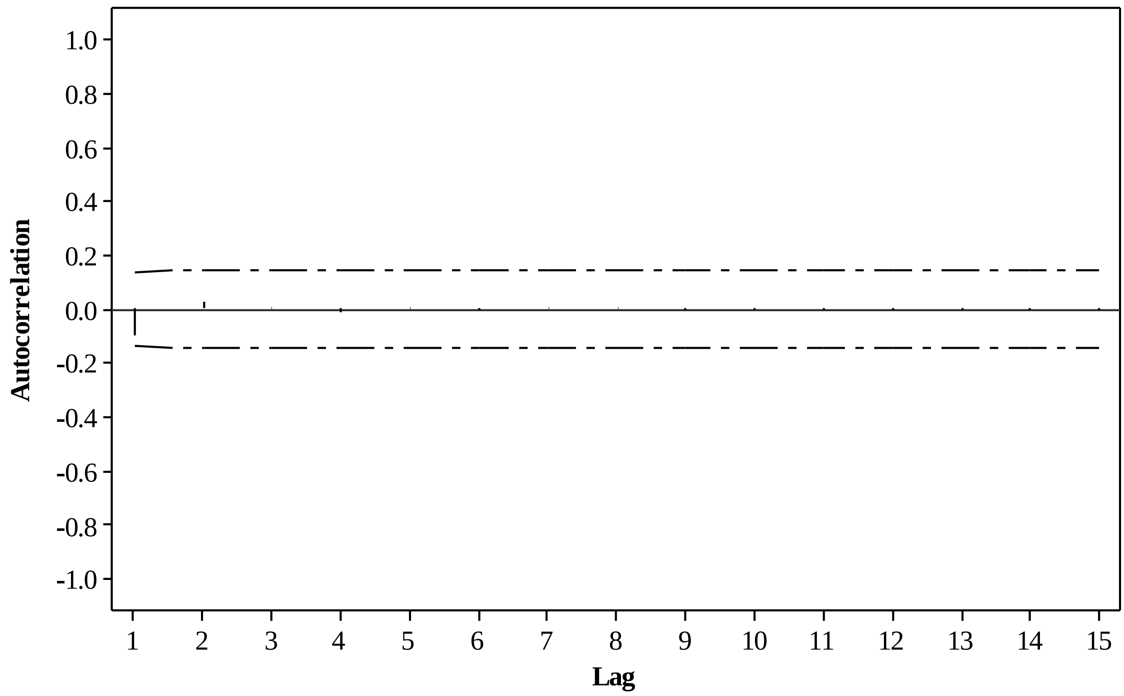
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
Partial Autocorrelation
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Lag

h)


Autocorrelation
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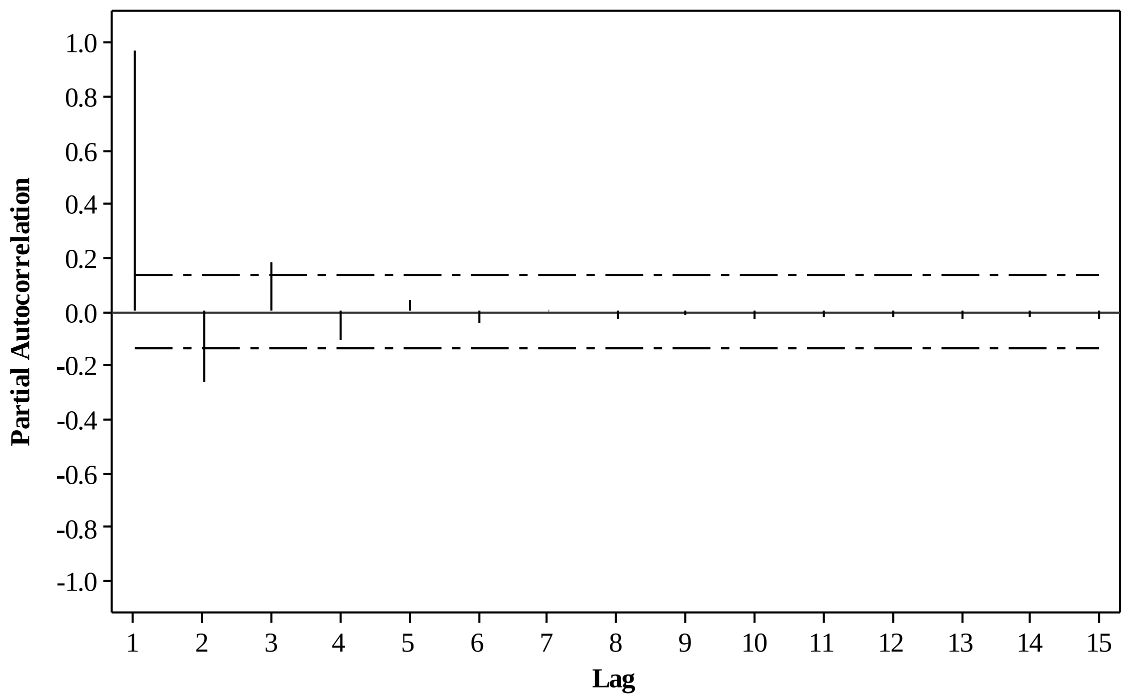
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Lag

i)


Partial Autocorrelation
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0.2
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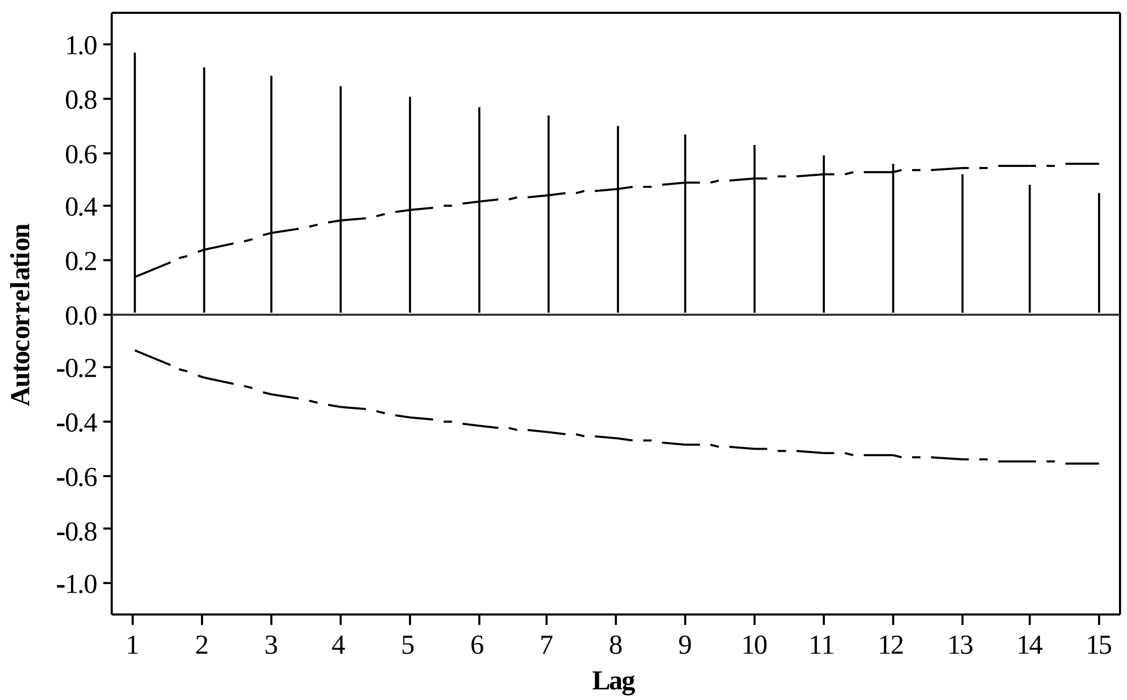
-0.8
-1.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Lag

j)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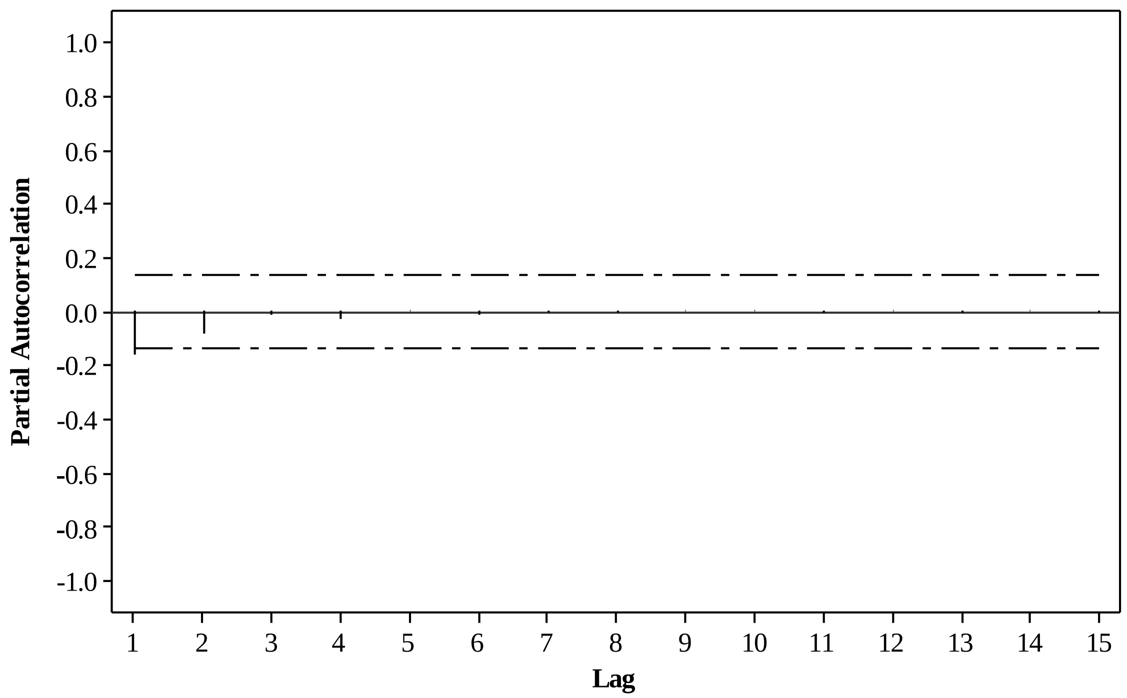
Autocorrelation
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Lag

k)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-0.6
-0.8
-1.0
Partial Autocorrelation
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Lag

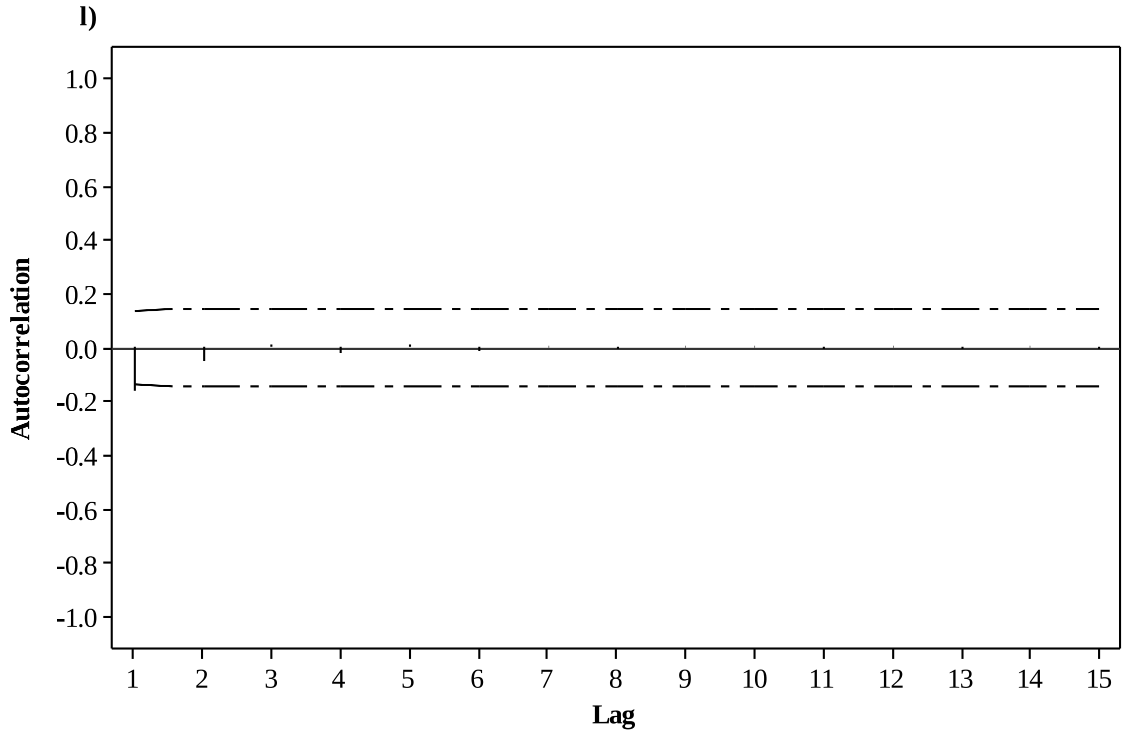


Figure 3

Autocorrelation test, PCF, ACF, real data, and residuals: a) partial autocorrelation function (PCF) for STR and real data; b) autocorrelation function (ACF) for STR and real data; c) partial autocorrelation function (PCF) for STR, residual, and ARIMA (0,1,1); d) autocorrelation function (ACF) for STR, residual, and ARIMA (0,1,1); e) partial autocorrelation function (PCF) for MRAC and real data; f) autocorrelation function (ACF) for MRAC and real data; g) partial autocorrelation function (PCF) for MRAC, residual, and ARIMA (0,1,1); h) autocorrelation function (ACF) for MRAC, residual, and ARIMA(0,1,1); i) partial autocorrelation function (PCF) for fuzzy and real data; j) autocorrelation function (ACF) for fuzzy and real data; k) partial autocorrelation function (PCF) for fuzzy, residual, and ARIMA(0,1,1); l) autocorrelation function (ACF) for fuzzy, residual, and ARIMA (0,1,1).

According to Table 4, the values of AIC, SBIC, and HQC were calculated at different (p, q) values within the range of $0 \leq p \leq 4$ and $0 \leq q \leq 4$. Similar results were obtained for all the three measures. The orders of the model were determined to be p = 0 and q = 1 based on the outputs of all the three APC methods.

Figure 4 shows the fitted ARIMA (0,1,1) time series on the outputs of all the three adaptive APC methods along with the residual values. The independent nature of the residuals of the outputs in all the three adaptive APC-controlled processes is shown in Figure 3. As can be seen, none of the PCF and ACF graphs which are drawn from the residual values exceeded the determined limits, indicating the fully independent nature of these observations. Therefore, it is possible to use the residual values which lack autocorrelation instead of the real data for the implementation of SPC. A repeat of the second step showed the abnormal nature of the residual values, as delineated in Figure 2.

The residual values resulting from the fitting of a time series to the output of the MPD process controlled by three different adaptive APC methods have been determined so far. These residual observations were independent and abnormal. Thus, it was necessary to select a suitable control chart in order to implement SPC on these observations. One of the best possible control charts was EWMA chart with a λ of 0.05, which could be used for abnormal and independent processes. As shown in Figure 5, this control chart was implemented on the outputs of all three APC control methods. According to this figure, during the occurrence of special causes, the process was out of control, so it was necessary to use the mud weight as a controllable input in order to control the process. In time ranges of 1–10 s and 100–110 s, the observations in the control chart were lower than the control limit. Therefore, at these times, it was necessary to add barite to the mud entering the oil well in order to increase the mud weight and control the process. In time ranges of 50–60 s and 150–160 s, the situation was reversed. At these times, the observations in the control charts were higher than the control limits, so it was required to reduce the amount of barite in the mud entering the oil well to reduce the mud weight and control the process. This method could compensate for APC's weakness during special causes and fully control the process. Another important factor in Figure 5 is that by using three graphs drawn based on the residual outputs of the three adaptive APC methods, it is possible to compare the performance of these APC methods. The results indicated that the fuzzy adaptive APC method had 30 out-of-control points which were significantly lower than those of the other two APC methods. Therefore, it is possible to conclude that the fuzzy adaptive APC method is superior when it comes to controlling the MPD process. This is also in agreement with the values of cost function tabulated in Table 5.

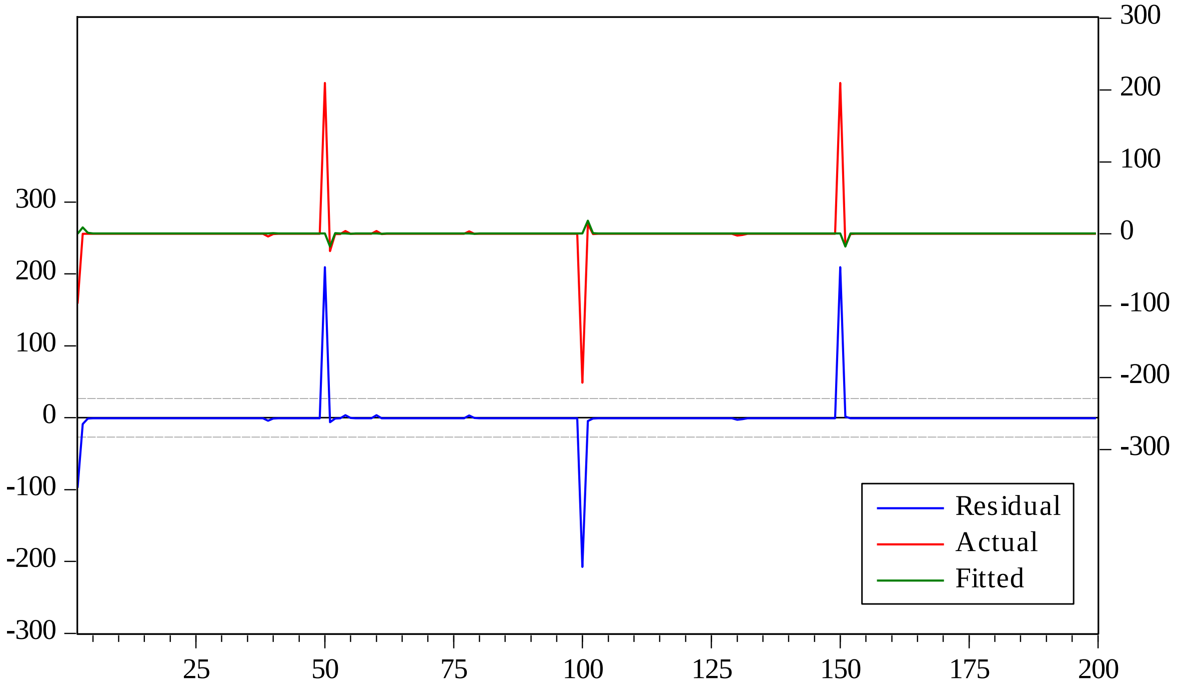
Table 4

Time series model.

Controller	Information criterion	-	***P* = 0**	***P* = 1**	***P* = 2**	***P* = 3**	***P* = 4**
STR	AIC	$q = 0$	-	9.4282	9.44	9.45	9.46
		$q = 1$	9.4281	9.44	9.45	9.46	9.47
		$q = 2$	9.44	9.45	9.46	9.46	9.47
		$q = 3$	9.45	9.46	9.46	9.47	9.48
		$q = 4$	9.46	9.47	9.47	9.48	9.49
	SBIC	$q = 0$	-	9.47789	9.50	9.53	9.56
		$q = 1$	9.47781	9.50	9.53	9.56	9.58
		$q = 2$	9.50	9.53	9.56	9.57	9.60
		$q = 3$	9.53	9.56	9.57	9.60	9.63
		$q = 4$	9.56	9.58	9.60	9.63	9.65
	HQC	$q = 0$	-	9.4483	9.46	9.48	9.50
		$q = 1$	9.4482	9.46	9.48	9.50	9.51
		$q = 2$	9.46	9.48	9.50	9.50	9.52
		$q = 3$	9.48	9.50	9.50	9.52	9.54
		$q = 4$	9.50	9.51	9.52	9.54	9.55
	ARIMA (0,1.1)	$p=0,\ d=1,\ q=1$		$D(BHP_t)=0.506624+\varepsilon_t-0.086852\varepsilon_{t-1}$			
MRAC	AIC	$q = 0$	-	8.9671	8.98	8.99	8.99
		$q = 1$	8.9667	8.98	8.99	8.99	9.00

Controller	Information criterion	-	P = 0	P = 1	P = 2	P = 3	P = 4
		$q = 2$	8.98	8.99	8.99	8.99	9.01
		$q = 3$	8.99	8.99	8.99	9.00	8.99
		$q = 4$	8.99	9.00	9.01	8.99	8.99
	SBIC	$q = 0$	-	9.0168	9.04	9.07	9.09
		$q = 1$	9.0163	9.04	9.07	9.09	9.12
		$q = 2$	9.04	9.07	9.08	9.11	9.15
		$q = 3$	9.07	9.09	9.11	9.14	9.14
		$q = 4$	9.09	9.12	9.15	9.14	9.16
	HQC	$q = 0$	-	8.9872	9.00	9.02	9.04
		$q = 1$	8.9868	9.00	9.02	9.04	9.05
		$q = 2$	9.00	9.02	9.03	9.04	9.07
		$q = 3$	9.02	9.04	9.04	9.06	9.05
		$q = 4$	9.04	9.05	9.07	9.05	9.06
	ARIMA (0,1.1)	$p = 0,\ d = 1,\ q = 1$	$D(BHP_t) = 0.223855 + \varepsilon_t + 0.249302\varepsilon_{t-1}$				
Fuzzy	AIC	$q = 0$	-	9.08	8.9756	8.9747	8.98
		$q = 1$	8.9735	8.98	8.9690	8.98	8.99
		$q = 2$	8.9727	8.9692	8.98	8.9754	8.98
		$q = 3$	8.9682	8.9753	8.98	8.98	8.99
		$q = 4$	8.98	8.9758	8.98	8.99	9.00
	SBIC	$q = 0$	-	9.13	9.04	9.06	9.08
		$q = 1$	9.02	9.04	9.05	9.08	9.10
		$q = 2$	9.04	9.05	9.07	9.09	9.12
		$q = 3$	9.05	9.07	9.09	9.12	9.14
		$q = 4$	9.08	9.09	9.12	9.14	9.17
	HQC	$q = 0$	-	9.10	9.00	9.00	9.02
		$q = 1$	8.99	9.00	9.00	9.02	9.03
		$q = 2$	9.00	9.00	9.02	9.02	9.04
		$q = 3$	9.00	9.01	9.03	9.04	9.05
		$q = 4$	9.02	9.02	9.04	9.05	9.07
	ARIMA(0,1.1)	$p = 0,\ d = 1,\ q = 1$	$D(BHP_t) = 0.881691 + \varepsilon_t + 0.587943\varepsilon_{t-1}$				

a)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-300
300
200
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0
-100
-200
-300
Residual
Actual
Fitted
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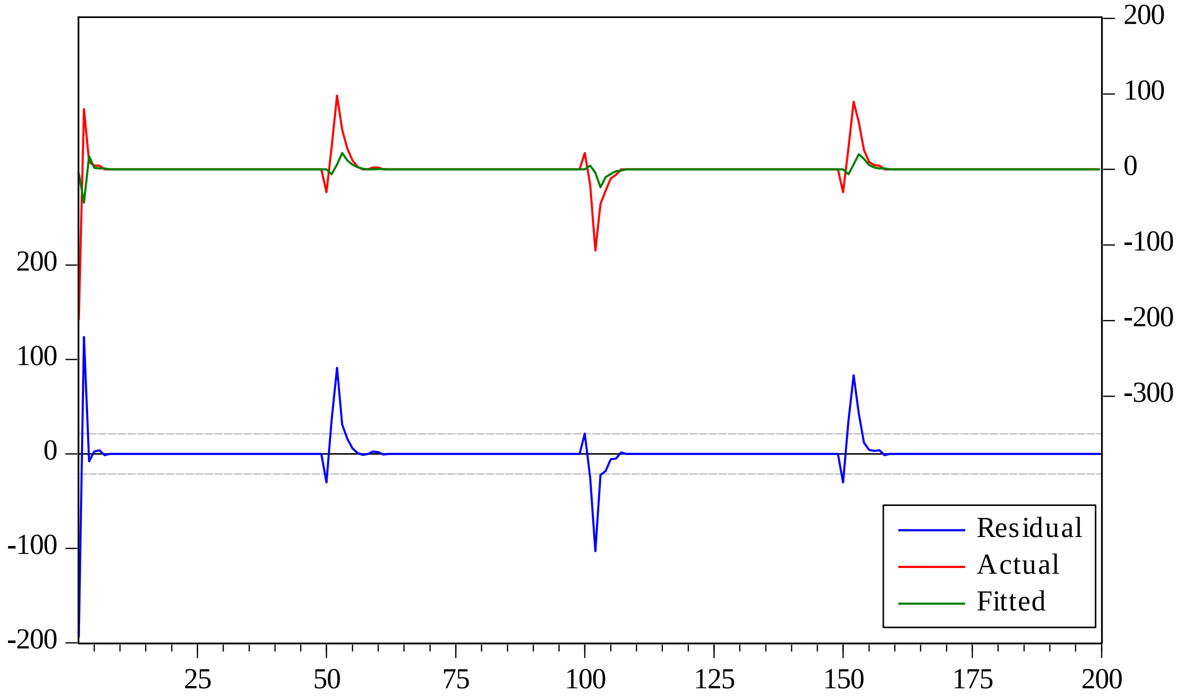
50
75
100
125
150
175
200

b)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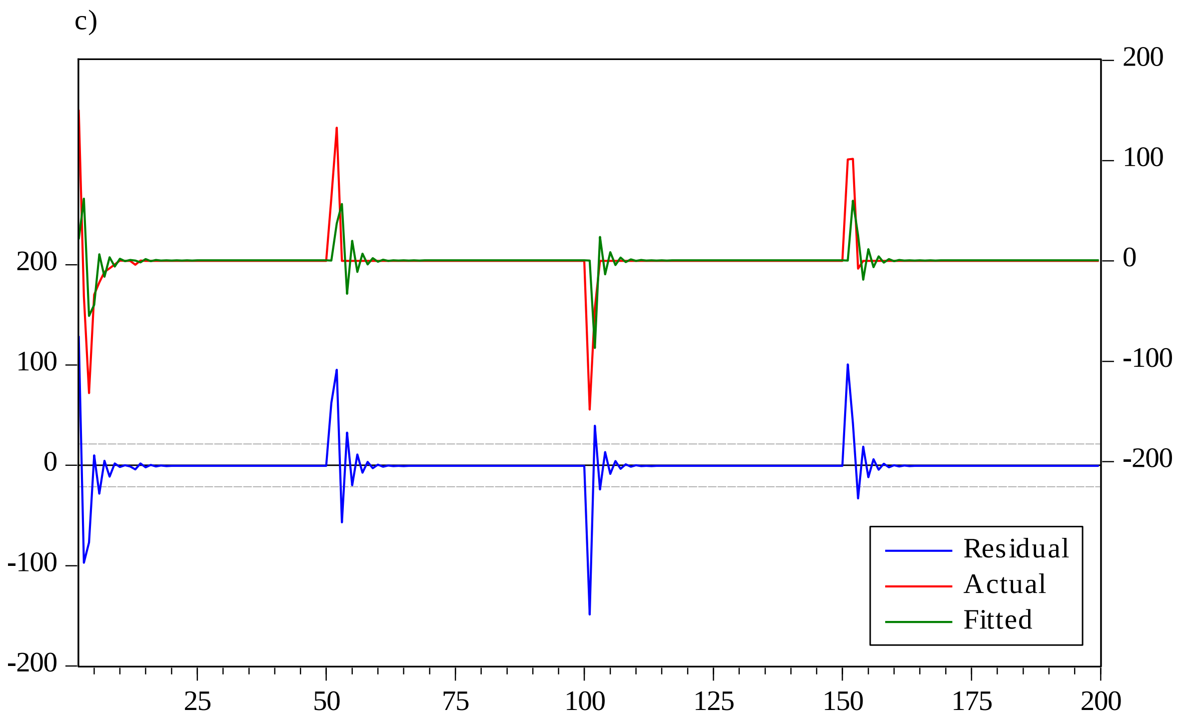
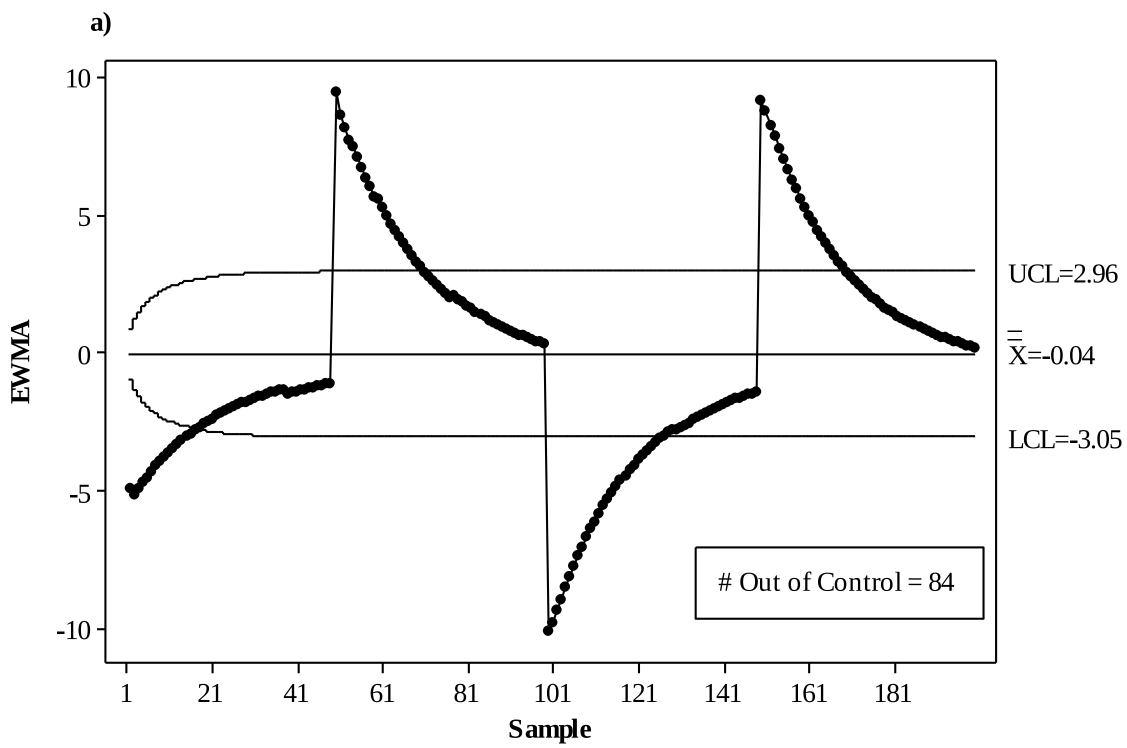


Figure 4

Time series model: residual, actual, and fitted model: a) STR; b) MRAC; c) fuzzy.



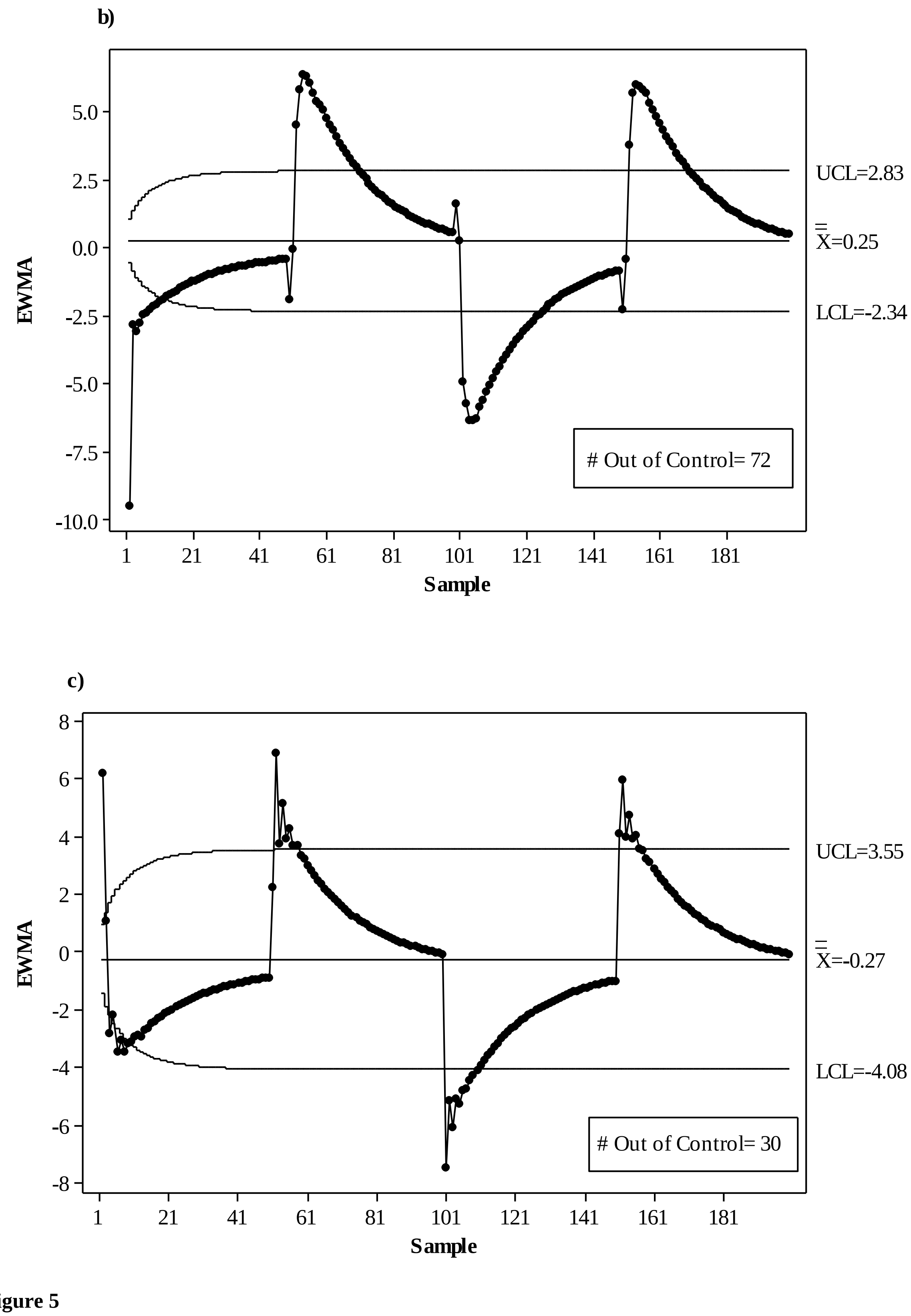


Figure 5

SPC, EWMA control chart, and residuals, $\lambda = 0.05$: a) EWMA chart of STR and ARIMA (0,1,1); b) EWMA chart of MRAC and ARIMA (0,1,1); c) EWMA chart of fuzzy and ARIMA (0,1,1).

Table 5

Cost function values: STR, MRAC, and fuzzy adaptive.

Cost function	ITSE	ISE	ITAE	IAE	MAE
STR	4.9024×10^9	4.8790×10^7	9.0348×10^8	8.0323×10^6	4.0161×10^4
MRAC	2.3187×10^9	2.0465×10^7	5.9052×10^7	5.5299×10^5	2.7649×10^3
FUZZY	1.7454×10^9	1.7505×10^7	4.8676×10^7	5.4031×10^5	2.7015×10^3

According to Table 5, the lowest percentage of error, based on the four IAE, ITAE, ISE, and ITSE functions, belonged to the adaptive fuzzy controller. Therefore, proper implementation of the SPC on the outputs of the APC can create a suitable IPC approach which can remove the common weaknesses of APC controllers and fully control the process; it would also make it possible to compare the performance of different APC methods.

Overall, the results indicated the superiority of the IPC approach, as compared to the APC, in controlling bit pressure in the MPD process. This approach can prevent any sudden pressure changes during the occurrence of random and special causes in the drilling operation, thereby preventing the kick phenomenon and oil well blowout. Thus, this approach can be an effective and important method for improving safety during drilling. Using this method can also help to reduce environmental and financial damage caused by oil well blowouts; therefore, it can be an important addition to the oil drilling industry.

5. Conclusions

SPC and control charts were employed in the present research for the first time in order to monitor and control the MPD process. It is shown that in the presence of random and special causes and under various operational conditions, applying SPC to the output of the APC can enhance confidence in controlling the process. Accordingly, a novel five-step approach was employed in this study to monitor and control the MPD process. The autocorrelated process data were converted into independent data based on this approach; this led to the determination of the instants in which the process exceeded the control limits. In such cases, parameters unusable in the APC, like the changes that may occur in the mud weight, can be fully compensated and controlled; as a result, any kick or formation damage and the resulting mud loss during drilling operations can be prevented. In addition, statistical process control was found to complement the engineering process control through this approach; this can yield an IPC approach providing simple solutions applicable to complex industrial processes. One of the innovations presented in this work involved using both a white box model for the APC implementation and a black box model for the SPC implementation. Furthermore, for the first time, this paper used control charts to not only improve the control of "APC monitoring processes", but also to evaluate the performance of different APC methods. The results of this evaluation approach were very similar to those of other evaluation methods often used for the APC. This means that control charts could be suggested as an alternative method to compare the outputs of different APC methods in future studies. Based on the new and previous evaluation criteria, the fuzzy adaptive APC method exhibited the best performance in controlling the MPD process during the drilling operation of oil wells.

Nomenclature

ACF	Auto correlation function
ADF	Augmented dickey fuller
AIC	Akaike's information criterion

APC	Automatic process control
ARIMA	Auto regressive integrated moving average
BHP	Bottom hole pressure
CUSUM	Cumulative sum
EWMA	Exponentially weighted moving average
HQC	Hannan-Quinn information criterion
IAE	Integral absolute error
IPC	Integrated process control
ISE	Integral square error
ITAE	Integral time absolute error
ITSE	Integral time square error
MAE	Mean absolute error
MMSE	Minimum mean squared error
MPD	Managed pressure drilling
MRAC	Model reference adaptive control
MSE	Minimum squared error
PCF	Partial autocorrelation function
PP	Phillips-Perron
RLS	Recursive least squares
SPC	Statistical process control
SBIC	Schwarz's Bayesian information criterion
ST	Sampling time
STC	Self-tuning controller
STR	Self-tuning regulators

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