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A Predictive Model for Unplanned Well Down in Heavy Oil Operations to Support Operational Decision-Making

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ABSTRACT

The decline in Heavy Oil (HO) production at PT XYZ is strongly influenced by unplanned well down events, which generate significant Loss Production Opportunity (LPO) and disrupt the achievement of production targets. This study aims to develop and compare two time series forecasting methods, ARIMA and Holt-Winters Exponential Smoothing (HWES), to predict future well down incidents caused by Mechanical Pumping Unit (MPU) failures. Model accuracy was evaluated using the Mean Absolute Percentage Error (MAPE), and the Seasonal ARIMA (2,2,1) Model was identified as the most accurate, achieving a MAPE value of 4.56 percent, significantly outperforming both HWES variants, which produced much higher errors (highest MAPE 27.37 percent). Using this model, the estimated financial loss in the Base Case scenario is projected at Rp 13.35 billion per year, with the worst sase scenario potentially reaching Rp 41.80 billion. The forecasting results provide substantial managerial value by supporting informed operational decision-making. Three key strategic implications are obtained. First, financial risk control can be strengthened by using the Upper Bound 95 percent as a basis for justifying MPU upgrade budgets. Second, production target planning becomes more realistic by incorporating predicted LPO values. Third, integrating LPO-based thresholds into KPI monitoring establishes an early warning system that shifts operational control from reactive to anticipatory.

Keywords: *ARIMA, Heavy Oil, Holt Winters Exponential Smoothing, Time Series Forecasting, Unplanned Well Down.*

Introduction

The demand for crude oil in Indonesia is critically high, but national oil production continues to face a sustained annual decline. This trend reflects a substantial challenge within the upstream oil and gas sector [1]. One of the oil and gas companies experiencing the impact of this production decline is PT XYZ. This company is one of the largest oil and gas corporations in Indonesia, managing a highly strategic oil and gas working area. One of the products from this working area is Heavy Oil (HO), which is a crude defined by its elevated viscosity and inherently poor flow characteristics [2]. In producing petroleum products, equipment called the Mechanical Pumping Unit (MPU) is required. The MPU is the most widely utilized artificial lift method in the petroleum industry for raising reservoir fluids to the surface [3]. The type of MPU utilized at PT XYZ is the Sucker Rod Pump (SRP). This system consists of two main components: the surface unit, which is the driving mechanism, and the downhole pump. SRPs are generally used in wells with low-to-medium flow rates and varying depths, making them a dominant technology in oil production operations across many oils field [4].

One factor contributing to the production decline is well-down incidents, where wells are temporarily shut due to technical or non-technical issues. These incidents create Loss Production Opportunity (LPO), representing potential oil output lost during downtime. Figure 1 presents a comparison between HO production and well down cases caused by MPU failures, showing a clear inverse relationship from January 2024 to May 2025. MPU failures fluctuate sharply while oil production consistently declines, indicating that MPU failures are a major source of LPO. The high uncertainty of these events also complicates operational planning, highlighting the need for a robust predictive model to assess future risks.

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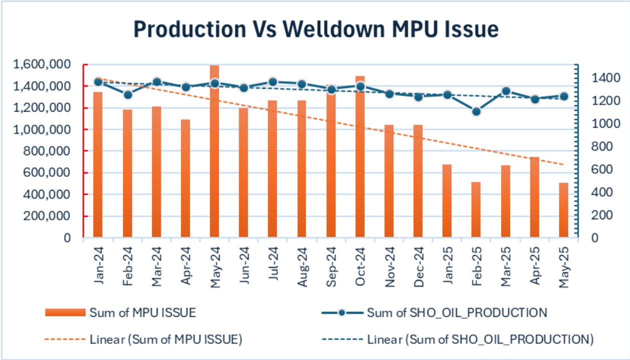

Figure 1. Production & well down trend of PT XYZ

This research develops and compares two time series forecasting methodologies, the Autoregressive Integrated Moving Average (ARIMA) and the Holt-Winters Exponential Smoothing (HWES). The ARIMA is a time series forecasting model that integrates elements from both the Moving Average (MA) and Autoregressive (AR) techniques. This model utilizes historical and current data to generate accurate short-term predictions [5]. Whereas the HWES method is a type of exponential smoothing utilized when the data exhibits both trend and seasonality in its pattern. The HWES method analyzes three distinct data components: it assigns greater weight to recent data or the data level, estimates the pattern of tendency or data trend, and estimates the seasonal pattern of the data, consequently yielding forecasts with a low error rate [6]. The combination of ARIMA and HWES is selected to address the complex characteristics of MPU-related well down data. ARIMA is used for its strength in modeling stationery and transformed non-stationary data, effectively capturing linear and short-term patterns. HWES complements this by handling data with trend and potential seasonality, producing adaptive forecasts for non-stationary and recurring patterns.

Research on predicting MPU-induced well down events, particularly in Indonesian heavy-oil operations, remains limited, with most studies focused on equipment reliability and maintenance rather than time-series forecasting. This gap indicates the absence of a predictive framework capable of converting historical data into reliable forecasts to reduce LPO.

This study compares ARIMA and HWES based on MAPE to determine the most accurate model for supporting data-driven mitigation strategies. As MPU failures are a major and increasing cause of well down incidents, and fall under the Production HO Department’s operational scope, the need for this analysis is critical. The results are expected to clarify failure dynamics, forecast future incidents, and guide proactive efforts to improve MPU reliability and overall production performance.

Research Methods

The research methods will be illustrated in the conceptual framework diagram in Figure 2.

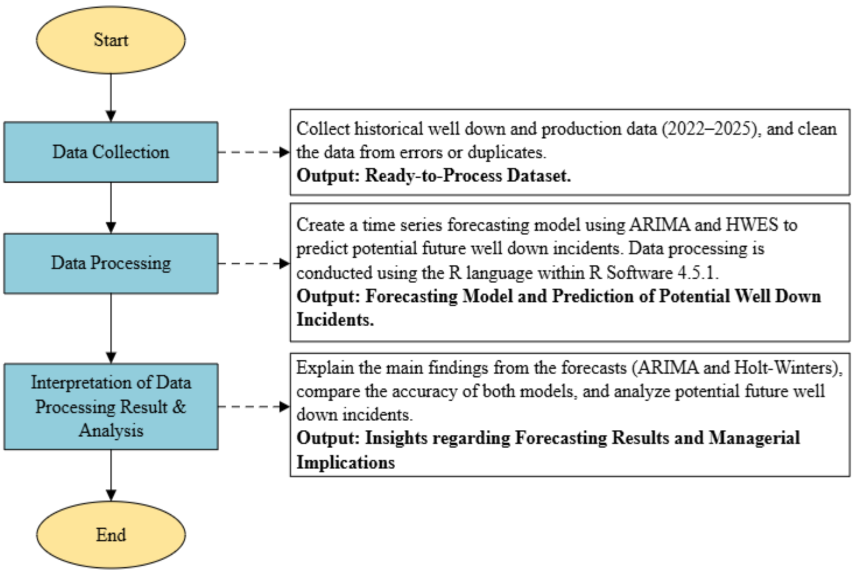

Figure 2. Conceptual framework

This research aims to identify and obtain the best and most accurate forecasting model (between the ARIMA and HWES methods) to predict future well down caused by MPU failure. Furthermore, it aims to formulate and recommend data-driven mitigation strategies derived from the results of the best and most accurate model, as an effort to enhance MPU reliability and optimize overall production performance. Based on Figure 2, the research methods comprise in four main stages.

Data Collecting

Data Collection involves gathering and cleaning historical well down and production data (2022–2025). The dataset prepared for processing is presented in Table 1.

Table 1. Data set of well down events

Month	Number of MPU Event			
	2022	2023	2024	2025
Jan	819	663	1276	642
Feb	500	380	1122	488
Mar	1074	570	1152	637
Apr	877	353	1034	710
May	976	417	1512	479
Jun	608	462	1139	383
Jul	533	599	1201	223
Aug	476	786	1204	
Sept	467	910	1342	
Oct	537	925	1418	
Nov	769	1020	988	
Dec	924	1334	987	

Table 1 presents the historical time series dataset used in this research, which contains records of well down events from January 2022 to July 2025. The inclusion of data up to July 2025 reflects the most recent operational observations available, ensuring that the forecasting models are trained using the latest patterns and volatility present in the field. This approach strengthens the robustness and relevance of the predictive results. In addition to the well-down data, Table 1 also incorporates production and Loss Production Opportunity (LPO) information. These supplementary datasets enable forecasting outputs to be directly linked with actual production performance and are specifically utilized to evaluate the potential LPO that may arise from MPU failures.

Table 2. Production data & LPO

Category	Production (BOPD) in Monthly	Loss Production Opportunity MPU Issue (BOPD) in Monthly
Average	44,900	632
Minimum	33,730	290
Maximum	49,956	993

Table 2 provides a statistical summary of the Production Data and LPO related to MPU events, measured in Barrels of Oil Per Day (BOPD) in monthly. Over the observed period, the average monthly production was 44,900 BOPD, with a minimum recorded production of 33,730 BOPD and a maximum reaching 49,956 BOPD. Concurrently, the LPO attributed specifically to MPU issues averaged 632 BOPD monthly. This LPO figure fluctuated significantly, ranging from a minimum loss of 290 BOPD to a peak loss of 993 BOPD, highlighting the considerable financial and operational impact caused by MPU failures

Data Processing

Data Processing focuses on developing time series forecasting models by implementing both ARIMA and HWES to predict future well down, following the identification of historical trends and seasonality. Last, Results Interpretation includes comparing the accuracy of both models and analyzing the best forecast to derive insights into future well down potential and frequency. This data processing is specifically conducted using the R language within R Software version 4.5.1. R is software developed to support statistical analysis, data science, and predictive modeling [7]. The selection of this Software was based on its characteristics and functionality. R allows users to freely modify, develop, and share code. This characteristic ensures that R continuously evolves in line with the needs of research and industry. One of R's main attractions is the availability of thousands of packages created by both the community and independent developers to support statistical analysis, data science, and predictive modeling. These packages encompass various functions, ranging from data processing and visualization to the development of web-based applications [8] [9].

Therefore, in this research, the process of creating the ARIMA and HWES models, up to the evaluation of both models, will be processed using this software.

Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) Model is often also referred to as the Box-Jenkins time series method. ARIMA demonstrates excellent accuracy for short-term forecasting [10]. The ARIMA model is one that completely disregards independent variables when generating a forecast. Instead, ARIMA utilizes the past and present values of the dependent variable to produce accurate short-term forecasts. ARIMA is suitable when the observations within a time series are statistically dependent on one another [11]. A crucial point to note is that most time series are non-stationary, and the Autoregressive (AR) and Moving Average (MA) aspects of the ARIMA model only pertain to stationary time series. Stationarity implies the absence of growth or declines in the data. The data must roughly maintain a horizontal level along the time axis. In other words, data fluctuations remain around a constant mean value, independent of time, and the variance of these fluctuations essentially remains constant over time [12]. Seasonality is defined as a pattern that recurs at fixed time intervals. For stationary data, the seasonal factor can be determined by identifying autocorrelation coefficients at two or three time-lags that are significantly different from zero. Autocorrelations that are significantly different from zero indicate the presence of a pattern within the data. To recognize the presence of a seasonal factor, one must observe high autocorrelation. To address seasonality, the general shorthand notation is [13]:

$$\text{ARIMA}\ (p,d,q)(P,D,Q)^{s} \tag{1}$$

Within this notation, the first three parameters, $(\boldsymbol{p}, \boldsymbol{d}, \boldsymbol{q})$, represent the non-seasonal component of the model. Conversely, the capital letters, $(\boldsymbol{P}, \boldsymbol{D}, \boldsymbol{Q})$ denote the seasonal component of the model, which captures the repeating patterns. Finally, $\boldsymbol{S}$ represents the total number of periods per season (e.g., $\boldsymbol{S} = \mathbf{12}$ for monthly data with annual seasonality).

```
=========== HASIL PERAMALAN ARIMA ========================================================

# Horizon Peramalan: 12 bulan (Agustus 2025 hingga Juni 2026)
h_future <- 12

# Forecast Model SARIMA Terbaik
forecast_sarima1_future <- forecast(m1_sarima, h=h_future)
forecast_sarima2_future <- forecast(m2_sarima, h=h_future)

# --- Menampilkan Hasil ---
print("--- Hasil Forecast SARIMA1 (Aug 2025 - Juni 2026) ---")
print(forecast_sarima1_future)
print("--- Hasil Forecast SARIMA2 (Aug 2025 - Juni 2026) ---")
print(forecast_sarima2_future)

# Grafik Plot Forecast ARIMA
# 1. Plot Forecast Model SARIMA1
plot(forecast_sarima1_future,
     main="Forecast Model SARIMA (2,2,1) (Aug 2025 - Juni 2026)",
     xlab="Periode",
     ylab="Jumlah Well Down")
# 2. Plot Forecast Model SARIMA2
plot(forecast_sarima2_future,
     main="Forecast Model SARIMA (1,2,0) (Aug 2025 - Juni 2026)",
     xlab="Periode",
     ylab="Jumlah Well Down")
```

Figure 3. Snippet of ARIMA data processing using R

Figure 3 provides a computational snippet detailing the preliminary steps and candidate model selection for the ARIMA process implemented in R. This code segment is presented as an excerpt from the complete script.

Holt-Winters Exponential Smoothing (HWES)

The Holt-Winters Exponential Smoothing (HWES) is a time-series forecasting method used to analyze data that exhibits both trend and seasonal patterns. Unlike simpler forecasting methods that only consider the level component, this method is a combination of the HWES and the Winter method. In the HWES, primary attention is given to estimating the trend component that develops over time, while the Winter method focuses on depicting the seasonal variations that recur over a specific period. Based on these two approaches, the HWES is capable of simultaneously capturing the long-term trend dynamics and the influence of seasonal cycles present in the time series data [14]. The HWES method is also known by the term Triple Exponential Smoothing because it involves three primary smoothing parameters. First, the parameter α (alpha) is used to smooth the level value or the fundamental mean of the data. Second, the parameter β (beta) plays a role in refining the trend changes that occur over time. Third, the parameter γ (gamma) is responsible for adjusting the seasonal pattern so that the model can capture periodic variations more accurately [15].

The HWES method essentially has two main forms: the additive model and the multiplicative model [16]. The Additive HWES Model is generally employed when the seasonal pattern in the time series is constant or is not influenced by the magnitude of the data values. The amplitude of the seasonal fluctuation tends to remain fixed and independent of both the average data level and the scale of the data being analyzed [17]. In contrast to the additive model, which assumes constant seasonal variation, the multiplicative model allows the magnitude of the seasonal component to adjust relative to the scale of the data [18].

```
=========== HASIL PERAMALAN HWES ==================================================

# Horizon Peramalan: 12 bulan (Agustus 2025 hingga Juni 2026)
h_future <- 12

# Forecast Model HWES
forecast_hwes1_future <- forecast(model_hwes_mult, h=h_future)
forecast_hwes2_future <- forecast(model_hwes_add, h=h_future)

print("--- Hasil Forecast HWES1 (Aug 2025 - Juni 2026) ---")
print(forecast_hwes1_future)
print("--- Hasil Forecast HWES1 (Aug 2025 - Juni 2026) ---")
print(forecast_hwes2_future)

# 1. Plot Forecast Model HWES Multiplikatif
plot(forecast_hwes1_future,
     main="Forecast Model HWES Multiplikatif (Aug 2025 - Juni 2026)",
     xlab="Periode",
     ylab="Jumlah Well Down")
# 2. Plot Forecast Model HWES Additive
plot(forecast_hwes2_future,
     main="Forecast Model HWES Additive(Aug 2025 - Juni 2026)",
     xlab="Periode",
     ylab="Jumlah Well Down")
```

Figure 4. Snippet of HWES data processing using R

Figure 4 provides a computational snippet detailing the execution of the HWES forecasting and visualization process implemented in R. This code segment is presented as an excerpt from the complete script.

Interpretation of Data Processing and Analysis

The Interpretation of Data Processing and Analysis section encompasses the critical process of comparing the forecasting results generated by both the ARIMA and HWES models. This comparison involves rigorously evaluating the predictive accuracy of the two models using the error measurement. Error measurement is used as a benchmark to compare the performance of various forecasting models under the same conditions [17]. One of the metrics utilized in error measurement is the Mean Absolute Percentage Error (MAPE). Mean Absolute Percentage Error (MAPE) is a measure widely used in quantitative forecasting to assess the accuracy level of prediction results. MAPE calculation is performed by taking the average percentage difference between the actual data and the forecasted value, where this difference is calculated in absolute terms, meaning it does not distinguish between positive and negative differences [19]. The MAPE formulation is detailed in the following equation:

$$\mathbf{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - F_t}{Y_t}\right| \times 100 \tag{2}$$

Where $\boldsymbol{n}$ represents the total number of observations used in the evaluation. $\boldsymbol{Y_t}$ is defined as the actual value of the time series at time $\boldsymbol{t}$ (where $\boldsymbol{t}$ = 1, 2, ..., $\boldsymbol{n}$), and $\boldsymbol{F_t}$ is the corresponding value predicted by the forecasting model at time $\boldsymbol{t}$. The formula computes the average of absolute percentage errors, providing a scale-independent measure of the model's predictive accuracy [19].

Results and Discussion

This section details the findings derived from the time series forecasting models developed in this study, followed by a comprehensive discussion of their implications. First, the result of data processing is data decomposition. Based on Figure 5, the decomposition confirms that the time series consists of three key components, namely a distinct trend, recurring seasonality, and a randomness component. The trend component shows a gradual decline at the beginning of 2022, followed by a steady upward movement throughout 2023, before reaching its peak in early 2024 and slowly declining again toward mid-2025. This pattern indicates that MPU well down incidents follow a medium-term structural movement rather than short-term fluctuations. The seasonal component displays repeated monthly variations, although the magnitude of these oscillations is relatively moderate, suggesting that recurring operational or environmental cycles contribute to periodic increases and decreases in MPU failures. The random component exhibits strong irregular fluctuations across the entire period, characterized by sharp rises and drops that do not follow any systematic pattern. In the context of MPU events, this randomness likely represents sudden equipment failures, unplanned operational disruptions, and unpredictable subsurface behaviors that cannot be anticipated using routine operational patterns.

The presence of a clear and evolving trend demonstrates that the data remain non-stationary in the mean and therefore requires differentiation for proper modeling. The combination of trend, seasonality, and substantial random noise confirms that the data are complex and unstable, making simple forecasting approaches inadequate. Consequently, the ARIMA and HWES methods are validated as suitable for addressing these characteristics. In addition, identifying the trend and seasonal structures provides operational benefits because it helps the company anticipate months with an increased likelihood of MPU failures

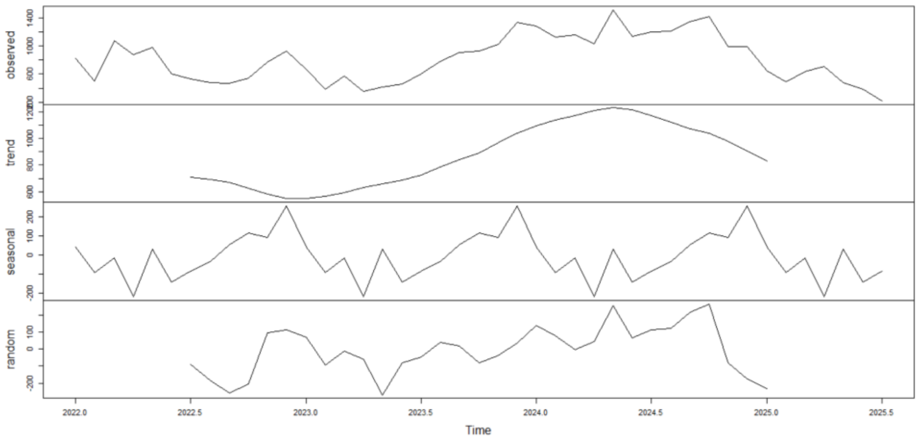

Figure 5. Data decomposition

Second, the results of data processing are presented through descriptive statistics. The descriptive statistics in Table 3 show significant fluctuation and dispersion. The number of monthly incidents spans a very wide range, from a minimum value of 223 to a maximum of 1,512, indicating a high level of volatility in MPU-related well down events. The mean value of 812 is slightly higher than the median of 786, suggesting that the data distribution is relatively symmetrical. Most importantly, the high standard deviation of 333.95, or approximately 41 percent of the mean, confirms that MPU incidents vary widely and remain unstable from month to month. This high level of volatility may be attributed to several factors such as instability in MPU performance, variations in reservoir behavior, fluctuating operational loads, or uneven maintenance effectiveness across periods. All repair activities are also reactive rather than proactive, which means sudden surges in failures cannot be prevented earlier and are only addressed after they occur. This condition forces the production team to operate under considerable uncertainty, increasing the risk of insufficient spare parts availability, limited manpower, and potential delays in handling sudden rises in MPU failure incidents.

Table 3. Statistic description of well Down caused by MPU failure

Category	Value of Statistic Description
Min	223
Max	1,512
Mean	812
Median	786
St.Dev	333.95

The application of the ARIMA model in this research is the Seasonal ARIMA (SARIMA), which is justified by the strong autocorrelation confirmed in the historical well down data. Initial data decomposition revealed a clear trend and seasonality, confirming that the time series was non-stationary and unsuitable for simple forecasting methods. To address this, the Box-Cox Transformation was first applied to stabilize variance (homoscedasticity) due to a high initial Augmented Dickey-Fuller (ADF) $P-value$. Subsequently, a Second Differentiation $(d = 2)$ was performed on the transformed data to eliminate the non-stationary trend. A second ADF test confirmed that this differentiated series was mean-stationary (with a P-value $= 0.01$), thereby setting the regular differentiation order (d) to 2. Based on the ARIMA model identification process conducted previously, two models were obtained: $\mathrm{SARIMA}(2,2,1)$ and $\mathrm{SARIMA}(1,2,0)$.

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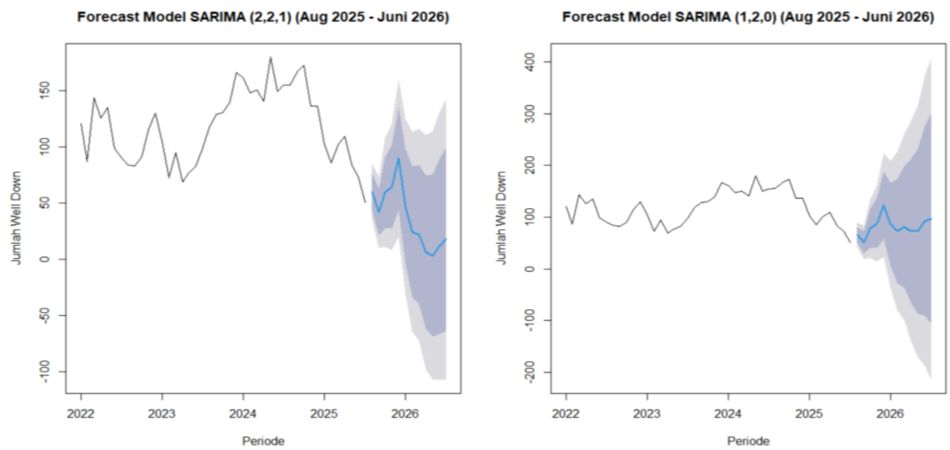

Figure 6. SARIMA forecasting output plot graph

The SARIMA Forecasting Output Plot (Figure 6) compares the historical data (black line) with the forecast (blue line) for the period August 2025 to June 2026. The SARIMA(2,2,1) Model (left) shows that the point forecast adheres to the historical seasonal pattern with a more stable trend. The blue line (forecast) remains within the gray area, which represents the confidence interval (CI). This model's CI is relatively narrow, indicating superior stability and reliability. Conversely, the SARIMA(1,2,0) Model (right) exhibits greater historical fluctuation. Most crucially, its confidence interval (CI) is significantly wider, even encompassing negative values. This extreme CI width verifies the high degree of uncertainty associated with this model. Therefore, based on its more controlled trend and narrower confidence interval, the SARIMA(2,2,1) Model is deemed more feasible and reliable for future prediction. narrower confidence interval increases the reliability of planning decisions, such as estimating LPO exposure, scheduling preventive workover, and determining realistic production targets.

Third, the HWES model was developed as an alternative to the ARIMA/SARIMA approach. The HWES Forecasting Output Plot (Figure 7) provides a visual comparison of the historical data against the forecasts for both HWES variants (August 2025 to June 2026). While the Multiplicative Model (left) shows a stable point forecast, its Confidence Interval (CI) is extremely wide, reaching from an upper bound near 3000 down to approximately -2000, signifying extreme uncertainty. Conversely, the Additive Model (right) presents a relatively narrower CI but still exhibits high volatility. Overall, both HWES models resulted in forecasts with a high degree of uncertainty. Therefore, a subsequent comparison of the MAPE accuracy metric is essential to determine the most reliable HWES model for future projections. These wide intervals indicate that HWES-based predictions are less suitable for operational decision-making, especially where precise planning of production, maintenance, or budgeting is required.

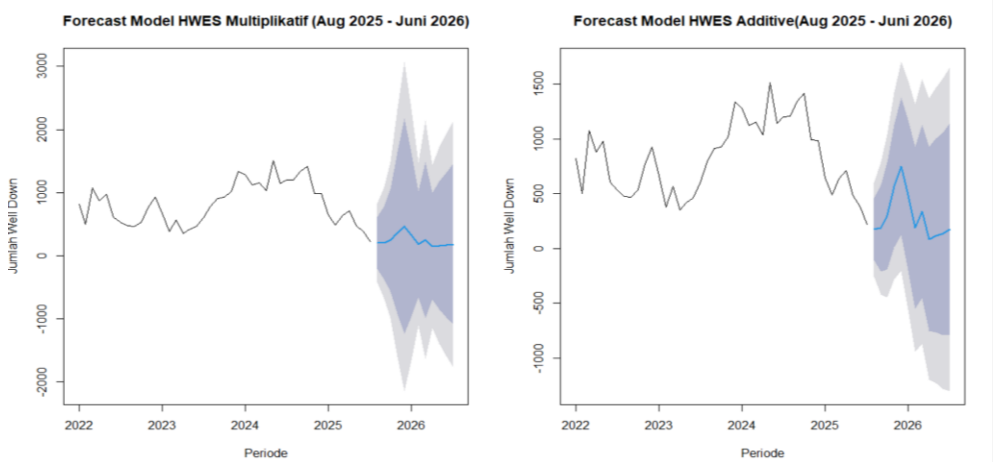

Figure 7. HWES forecasting output plot graph

Subsequently, the determination of the best model is carried out through a comparison of in-sample accuracy metrics (fitting accuracy) such as the Mean Absolute Percentage Error (MAPE). Based on the lowest MAPE value, the single best model will be selected and utilized as the primary basis for drawing final forecasting conclusions in this study. Based on Table 4, the smallest MAPE value is 4.5619%, achieved by the SARIMA(2,2,1) model. This low percentage indicates that the SARIMA(2,2,1) model has the highest fitting accuracy among all candidates and is therefore selected as the best and most reliable model for forecasting future well down events. The results of this research are consistent with previous studies, where the error generated by ARIMA was significantly better than that of HWES [20]. With its high accuracy, the SARIMA (2,2,1) model provides a dependable foundation for LPO risk quantification, early warning indicators, and budget allocation strategies.

Table 4. MAPE of forecasting model

Model	MAPE (%)
SARIMA (2,2,1)	4.56
SARIMA (1,2,0)	5.22
HWES Multiplicative	27.37
HWES Additive	20.91

Based on the MAPE results, the best Forecasting Results for the SARIMA(2,2,1) model is as follows:

Table 5. The best forecasting result

Periode	SARIMA (2,2,1)				
	Point Forecast	Lower Bound (80%)	Upper Bound (80%)	Lower Bound (95%)	Upper Bound (95%)
Aug-25	59.906	43.415	76.396	34.685	85.126
Sep-25	41.636	20.983	62.290	10.050	73.223
Oct-25	59.046	27.567	90.524	10.903	107.188
Nov-25	64.163	27.361	100.965	7.879	120.446
Dec-25	89.786	43.967	135.604	19.712	159.859
Jan-26	47.072	-4.049	98.194	-31.111	125.256
Feb-26	24.241	-33.843	82.326	-64.591	113.074
Mar-26	21.962	-39.859	83.783	-72.586	116.510
Apr-26	5.972	-62.243	74.187	-98.354	110.298
May-26	3.367	-68.638	75.373	-106.756	113.491
Jun-26	11.608	-66.400	89.615	-107.694	130.909
Jul-26	18.140	-63.704	99.984	-107.030	143.309

The final forecasting results from the selected SARIMA(2,2,1) model project the potential LPO reduction achievable through proactive mitigation efforts. The forecast reveals a substantial potential average reduction of 91.719 BOPD under the Conservative Scenario, which translates to a maximum financial risk of \$2.50 Million (or Rp 41.80 billion) over the forecast period if well down incidents are not adequately controlled. These robust predictive outputs form the foundation for four strategic managerial pillars are Financial Risk Control (by allocating budgets based on the worst-case scenario loss), Production Target Planning (using the Point Forecast to set realistic targets), KPI Integration for Early Warning (shifting performance control from reactive to predictive), and Justifying Operational Investment (prioritizing preventive maintenance in months with the highest forecasted LPO to maximize production gains).

Beyond supporting strategic planning, the forecasting results also provide clear operational benefits. The predicted LPO values help identify months with higher MPU-failure risk, enabling maintenance teams to schedule preventive work more effectively and avoid unplanned downtime during high-production periods. These insights also improve manpower and spare-parts planning, reducing the likelihood of emergency repairs and operational disruptions. The quantified financial risk strengthens the justification for preventive maintenance spending, allowing management to prioritize interventions that deliver the greatest cost avoidance. Incorporating forecast outputs into routine production monitoring enables earlier anomaly detection, allowing operators to initiate corrective actions before failures escalate. Additionally, aligning spare-parts procurement with predicted failure patterns improves inventory efficiency and minimizes stockouts. Overall, the forecasting model enhances coordination across Production, Maintenance, Planning, and Finance, supporting more proactive decision-making and improving the company's ability to manage MPU reliability and mitigate LPO effectively.

Conclusion

The forecasting of well down incidents caused by MPU failure was successfully performed using both ARIMA/SARIMA and Holt-Winters Exponential Smoothing (HWES), with the SARIMA(2,2,1) Model proven to be the most accurate model (MAPE 4.5619%) after significantly outperforming all other candidates (HWES Multiplicative MAPE: 27.3697%). This accurate model allows for the estimation of LPO and uncertainty (CI 95%) for 12 months, and its results are translated into structured strategic recommendations covering financial risk control, production target planning, KPI integration for early warning, and the justification for investing in MPU upgrades or Predictive Maintenance (PdM) programs to mitigate LPO. Future research should build upon this foundation by comparing the SARIMA(2,2,1) Model with advanced non-linear techniques like LSTM or Prophet, and by expanding the analysis to model simultaneous losses across multiple MPU locations using methods like Vector Autoregression (VAR).

In addition to these analytical contributions, the forecasting outcomes also provide practical managerial value that directly strengthens operational decision-making. The ability to predict monthly well down risks enables production supervisors to prepare manpower, logistics, and spare parts allocation more efficiently, reducing emergency responses and minimizing operational disruptions. The quantified LPO risk supports budget holders in planning cost-avoidance strategies and prioritizing high-impact reliability improvements. Forecast-based early warning indicators also shift operational control from a reactive posture toward a more anticipatory one, allowing field teams to take preventive actions before failures escalate. For senior management, the forecasting model establishes a clear data-driven basis for investment justification, especially for interventions aimed at improving MPU reliability, optimizing maintenance strategies, and supporting long-term production stability. Collectively, these managerial implications demonstrate that the forecasting model is not only technically accurate but also strategically valuable in enhancing decision quality across operational, financial, and planning functions

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