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Evaluating DRP Implementation for 3 KG LPG Distribution Efficiency

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Abstract

This study evaluates the effectiveness of Distribution Requirements Planning (DRP) integrated with ARIMA time series forecasting to support delivery scheduling decisions and the determination of minimum inventory levels. As a representative case study, a 60-month sales series of Ultra-Pure Water was used to simulate fluctuating retail demand across the agent–depot network. The Augmented Dickey–Fuller test confirmed stationarity (p = 0.0142), allowing candidate ARIMA (p, 0, q) models to be evaluated using ACF/PACF and information criteria. The best model was ARIMA (1,0,1), which had the lowest Akaike Information Criterion and passed diagnostic tests (normal residuals, no autocorrelation, no heteroscedasticity), making it suitable for operational forecasting. Projection results indicated a stable demand pattern and yielded a safety stock threshold of 733.24 units/month (equivalent to 24.44 units/day) as a reference for inventory control. These findings demonstrate that the DRP–ARIMA integration can enhance supply reliability and distribution efficiency, particularly for subsidized goods such as 3 kg LPG, with practical implications for determining adaptive inventory levels, delivery routes and frequency, and upstream–downstream coordination. Theoretically, this study provides additional empirical evidence on the use of quantitative forecasting models to operationalize DRP in the energy sector, while also providing a foundation for replication in other critical commodities.

Keywords: distribution requirements planning, 3 kg LPG distribution, logistics efficiency, supply chain, energy companies.

INTRODUCTION

The distribution of 3 kg LPG gas is one of the important aspects in the energy industry, particularly in meeting the needs of households and small businesses in Indonesia. Efficiency in distribution becomes a key factor in ensuring the availability and price stability of products in the market. One method that can be applied to optimize distribution is Distribution Requirements Planning (DRP), a planning approach that focuses on demand forecasting and systematic inventory management to avoid shortages or excess stock (Ballou, 2004).

The DRP method has been applied in various industries to improve supply chain efficiency, reduce logistics costs, and increase customer satisfaction (Christopher, 2016). In the context of 3 kg LPG distribution, this method has significant potential to enhance the

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effectiveness of deliveries from agents to depots and reduce the likelihood of distribution delays that could affect supply stability (Chopra & Meindl, 2019).

However, the implementation of the DRP method in 3 kg LPG distribution still faces various challenges, such as infrastructure limitations, demand variability, and strict government regulations in subsidized goods distribution (Bowersox et al., 2013). Other factors that need to be considered include the role of technology in supporting DRP implementation (Simchi-Levi et al., 2007), demand-based distribution planning (Ross, 2015), and an integrated supply chain planning approach (Stadtler, 2015).

The application of the DRP system also depends on optimal logistics and distribution management aspects (Rushton et al., 2022), appropriate supply chain strategies (Taylor, 2004), and the implementation of efficient inventory control systems (Pfohl, 2004). In addition, the success factors in DRP implementation are also related to coordination between suppliers, distributors, and retailers (Lambert et al., 1998), as well as the utilization of information technology in distribution systems (Jonsson, 2008).

From an academic perspective, previous research highlights various challenges and opportunities in the application of DRP, including in the context of logistics optimization (Mentzer et al., 2001), inventory control strategies (Axsäter, 2015), and the application of mathematical models in distribution (Ghiani et al., 2013). Other factors of concern include operational efficiency in distribution management (Slack et al., 2021), the application of lean concepts in the supply chain (Hopp & Spearman, 2011), and the influence of supply chain strategies on the competitiveness of the energy industry (Frazelle, 2002).

This study aims to evaluate the implementation of the DRP method in optimizing the distribution of 3 kg LPG gas in energy companies, both from a theoretical review and its field application. Using an analytical approach and case study, this research is expected to provide insights into the advantages and limitations of the DRP method in supporting more efficient and effective distribution (Chopra, 2019).

Thus, this study will contribute to energy companies in designing better distribution strategies and to stakeholders in understanding the importance of supply chain optimization in the distribution of subsidized goods (Waters, 2007).

METHOD

This study employs a mixed-methods approach combining quantitative and qualitative methods, using case study and simulation techniques, to develop an optimization model for 3 kg LPG distribution based on Distribution Requirements Planning (DRP). The initial stage of the research focuses on preparation and literature review, which includes systematic problem and research objective identification, conceptual framework development, and initial hypothesis formulation. Subsequently, the study collects and reviews scientific literature, journals, industry reports, and policy documents related to energy distribution, supply chain efficiency, and the implementation of the DRP method. At this stage, a list of key parameters and performance indicators to be used in model design is also prepared, along with the determination of analytical tools and methods, including logistics simulation software.

Data collection is conducted through a combination of secondary and primary data. Secondary data are obtained from official LPG distribution reports, government statistical data, energy regulations, and relevant previous publications. Meanwhile, primary data are collected through in-depth interviews and structured surveys with industry actors, such as distribution agents, logistics operators, and 3 kg LPG consumers, to gain direct insights into demand patterns, operational constraints, and actual distribution practices. This approach

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allows the study to gain a comprehensive understanding of the LPG distribution conditions in the field.

After data collection, the next stage is the design of the DRP optimization model. The distribution model is designed by integrating DRP principles while considering actual demand dynamics and distribution capacity. Key variables incorporated into the model include historical demand data, stock availability, vehicle and warehouse capacity, delivery schedules, and logistics cost structures. Additionally, several distribution scenarios are developed to test the model's flexibility under real conditions, such as demand surges or supply limitations.

The simulation and model validation stage involves testing the designed model using logistics software. Validation is conducted by comparing the simulation results with actual data and conventional scenarios to measure the model's effectiveness in terms of delivery accuracy, supply reliability, and cost efficiency. Sensitivity testing is also performed to assess the model's response to changes in key input parameters, ensuring that the model can be adapted to varying operational conditions.

Analysis and evaluation are carried out both quantitatively and qualitatively. Quantitative analysis includes measuring performance indicators such as total distribution cost reduction, improved demand planning accuracy, and time and resource efficiency in distribution. Qualitative analysis is conducted through follow-up interviews with stakeholders to assess operational impact and acceptance of the proposed model. Based on the evaluation results, strategic recommendations are developed for practical implementation in energy distribution companies.

The final stage of the research involves publication and dissemination of the results. The final research outcomes will be compiled into a scientific article and published in a non-Q Scopus-indexed international journal. Dissemination is also carried out through scientific conferences, industry discussion forums, and policy reports directed at government agencies and distribution companies. The research output is expected to support the achievement of Sustainable Development Goal (SDG) 9: Industry, Innovation, and Infrastructure, as well as support the University's Key Performance Indicators (KPI) in research and industry partnerships.

RESULT AND DISCUSSION

Descriptive Statistics

During the observation period, the Ultra-Pure Water sales data, covering 60 months or 240 weeks, showed a minimum value of 18.00 and a maximum value of 42.00, with a standard deviation of 5.21, indicating variability in sales. Below is a presentation of the descriptive data for the observation period.

Table 1. Descriptive Statistics of Ultra-Pure Water Sales

Minimum	Median	Mean	Maximum
18,00	32,00	33,11	42,00

Sales Data Stationarity

After obtaining the required data, the researcher processed the data starting with a stationarity test. Differencing was applied if the data were found to be non-stationary. If the data were already stationary, the next steps included order determination, assumption testing, model interpretation, and forecasting. From the forecast data, a safety stock analysis

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was conducted to determine the minimum inventory level for the Ultra Pure Water product.

The stationarity processing of the sales data was performed using the E-Views application, where the data plot graph can be seen in Figure 1.

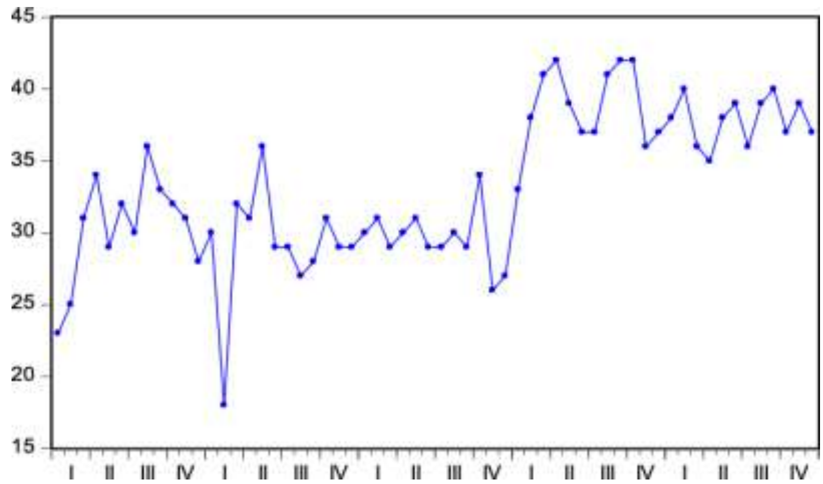

Figure 1. 24-Month Data Plot

The total number of Ultra-Pure Water product sales transactions from the first quarter was 1,995 packs. From the plot and subsequent data graph, a stationarity test was conducted using the Augmented Dickey-Fuller (ADF) test, resulting in a probability value of 0.0142. Using the hypothesis that the probability value = 0.0142 < 0.05, it can be concluded that the sales data is already stationary according to the ADF test.

Table 2. Stationarity of Sales Data Using the Augmented Dickey-Fuller Test

Null Hypothesis: Sales has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		T-Statistic	Prob.*
Augmented Dickey-Fuller Test Statistic		-3.415744	0.0142
Test Critical Values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

MacKinnon (1996) one-sided p-values.

Since the ADF test shows a p-value of 0.0142, which is less than 0.05, H1 is accepted, indicating that the sales data is stationary at this level. The d component of the ARIMA (p, d, q) model is 0 because the data is stationary at this level. Subsequent analysis will use ARIMA (p, 0, q).

Next, verify p and q. After obtaining stationary data, determine the order, or degrees, of p and q. Calculate the ACF and PACF values to establish the order. For accurate p and q values in ARIMA using EViews, create ACF and PACF diagrams using a correlogram. ACF is the autocorrelation function, while PACF is the partial autocorrelation function. The ACF determines q or MA, and the PACF determines p or AR.

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Table 3. Sales Data Correlogram

Lag	Autocorrelation (AC)	Partial Correlation (PAC)	Q-Stat	Prob
1	0,475	0,475	29.501	0.000
2	0,397222222	0,135416667	50.456	0.000
3	0,302083333	-0.020	62.805	0.000
4	0,338888889	0,196527778	78.641	0.000
5	0,320833333	0.070	93.080	0.000
6	0,295833333	-0.017	105.57.00	0.000
7	0,270833333	0.078	116.26.00	0.000
8	0,219444444	-0.090	123.38.00	0.000
9	0,230555556	0.087	131.42.00	0.000
10	0,178472222	-0.086	136.36.00	0.000
11	0,197222222	0.062	142.49.00	0.000
12	0,194444444	0.099	148.56.00	0.000
13	0,178472222	0.072	153.79	0.000
14	0,088194444	-0.190	155.09.00	0.000
15	0.093	0.024	155.80	0.000
16	0.082	-0.028	157.00.00	0.000
17	0.085	-0.037	157.62	0.000
18	0.014	-0.120	157.70	0.000
19	-0.010	0.038	157.96	0.000
20	-0.090	-0.140	158.46.00	0.000
21	-0.080	0.029	158.64	0.000
22	-0.080	-0.072	159.96	0.000
23	-0.140	-0.140	161.14.00	0.000
24	-0.210	-0.130	165.89	0.000
25	-0.210	-0.123	168.29.00	0.000
26	-0.250	-0.057	179.76	0.000
27	-0.250	0.057	187.22.00	0.000
28	-0.190	0.080	191.76	0.000

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The EViews correlogram shows that the autocorrelation function (ACF) diagram on the left reaches the limit only at the third lag. At Lag-1 and Lag-2, the values remain outside the White Noise range, indicating that the MA or q component in the ARIMA (p, d, q) model could be 0, 1, or 2. This differs from the PACF diagram on the right, where the limit occurs at the second lag. At Lag-1, the value remains outside the White Noise threshold, while at Lag-2, it falls within the White Noise range. Consequently, the potential AR or p component ranges between 0 and 1.

ARIMA Model Identification

Next, the ACF and PACF values are used to determine the p and q parameters, leading to potential ARIMA (p, d, q) model configurations based on the stationarity test and correlogram results, including ARIMA (0,0,1), (0,0,2), (1,0,0), (1,0,1), or (1,0,2). There are five potential models that can be developed. Additionally, to select the optimal model among the options, an overfitting technique is applied by evaluating each potential model.

ARIMA Model Estimation

The stationary data indicates that ARIMA model estimation is feasible. The amount of differencing required to achieve stationarity corresponds to the d order in ARIMA, which is zero in this case. Initial ARIMA model identification is performed considering parsimony criteria. The ARIMA (p, d, q) model is used to select the appropriate model, specifically the one with the lowest Akaike Information Criterion (AIC) and significance levels close to zero, to obtain preliminary ARIMA values.

Table 4. ARIMA Model (0,0,1)

Dependent Variable: Sales
Method: Least Squares
Sample: 20M01 2023M12
Included observations: 60

Variable	Coefficient	Std. Error	T-STatistic	Prob.
C	33.11149	0.824776	40.14601	0.0000
MA (1)	0.469819	0.114152	4.114745	0.0001
Akaike info criterion	5.816155			
Schwarz criterion	5.885967			

Table 5. ARIMA Model (0,0,2)

Dependent Variable: Sales
Method: Least Squares
Sample: 20101 2023M12
Included observations: 60

Variable	Coefficient	Std. Error	T-Statistic	Prob.
C	33.12434	0.870879	38.03554	0.0000
MA (2)	0.518983	0.102819	45.047531	0.0000
Akaike info criterion	5.863342			
Schwarz criterion	5.934244			

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Table 6. ARIMA Model (1,0,0)

Dependent Variable: Sales
Method: Least Squares
Sample (adjusted): 2M02 2023M12
Included observations: 60

Variable	Coefficient	Std. Error	T-Statistic	Prob.
C	33.81901	1.531069	22.08849	0.0000
AR(1)	0.691096	0.090435	7.641888	0.0000
Akaike info criterion	5.429396			
Schwarz criterion	5.499821			

Table 7. ARIMA Model (1,0,1)

Dependent Variable: Sales
Method: Least Squares
Sample (adjusted): 20M02 2023M12
Included observations: 60

Variable	Coefficient	Std. Error	T-Statistic	Prob.
C	34.60318	2.211854	15.64442	0.0000
AR(1)	0.854591	0.084525	10.11045	0.0000
MA(1)	-0.360927	0.164170	-2.198495	0.0321
Akaike info criterion	5.403269			
Schwarz criterion	5.508906			

Table 8. ARIMA Model (1,0,2)

Dependent Variable: Sales
Method: Least Squares
Sample (adjusted): 20M02 2023M12
Included observations: 60

Variable	Coefficient	Std. Error	T-Statistic	Prob.
C	33.72674	1.508681	22.35512	0.0000
AR(1)	0.629599	0.106543	5.909354	0.0000
MA(2)	-0.206057	0.141789	1.453263	0.1517
Akaike info criterion	5.419413			
Schwarz criterion	5.525050			

Based on the ARIMA model estimation for the Ultra-Pure Water product, the best model obtained is ARIMA (1,0,1).

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Forecasting with ARIMA (1,0,1)

The dataset used to identify the ARIMA model is applied to project sales in order to determine the MAPE value. After selecting the optimal model in this ARIMA study using EViews, the next step is to generate forecasts. In this case, sales are projected for the upcoming year. The results of the forecast are as follows:

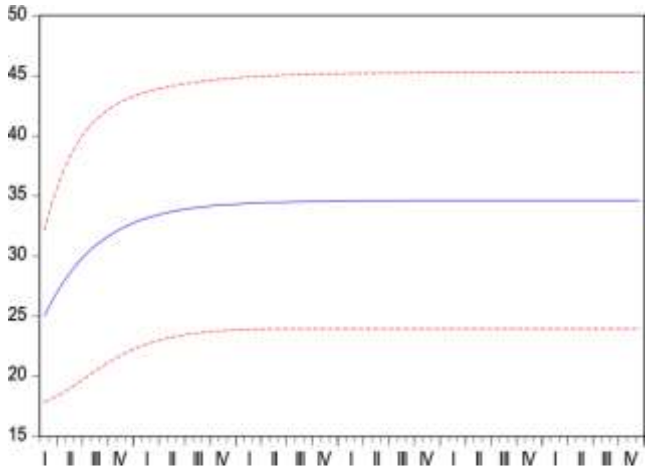

Figure 2. ARIMA Forecast Output

The blue line, which represents the projected sales, lies between the two red lines, indicating that the forecast is stable.

Model Assumption Analysis

Next, the assumption tests in this model include normality, autocorrelation, and heteroskedasticity.

Normality Assumption

1. The normality test is then conducted, as shown in the figure below.

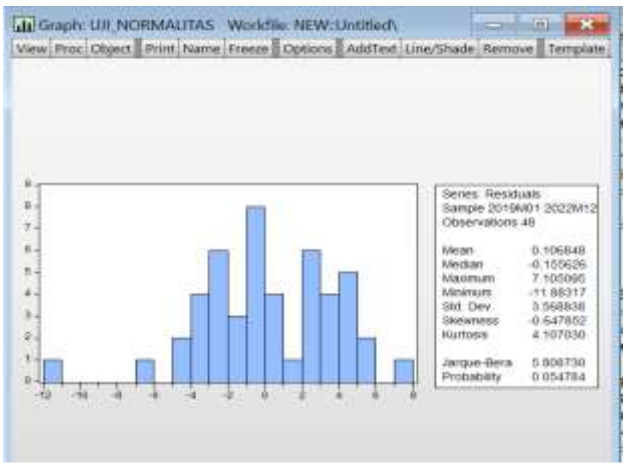

Figure 3. Normality Test of Data

The Jarque-Bera residual normality test shows a p-value of 0.054784, which exceeds 0.05, indicating a normal distribution for the sales data.

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2. Autocorrelation Assumption

Next, the autocorrelation test is conducted, as shown in the following figure.

Table 9. Autocorrelation Correlogram

Lag	Autocorrelation (AC)	Partial Correlation (PAC)	Q-Stat	Prob
1	0.010	0.010	0.0067	-
2	0.062	0.062	1,74166667	-
3	-0.246	-0.249	41.533	0.042
4	0.062	0.071	44.038	0,07708333
5	0,08611111	0,1125	54.246	0,09930556
6	0.064	-0.017	57.026	0,15416667
7	-0.157	0,12638889	74.026	0,13333333
8	-0.090	-0.044	79.723	0,16666667
9	0.074	0.052	83.627	0,20972222
10	-0.169	-0.115	10.451	0,16319444
11	0.008	-0.068	10.455	0,21875
12	0.090	0,09097222	11.070	0,24444444
13	0.055	-0.033	11.304	0,29027778
14	-0.030	0.084	11.378	0,34513889
15	-0.042	-0.087	11.522	0,39375
16	0.059	0.066	12.141	0,46388889
17	0.062	0.066	12.600	0,4875
18	-0.072	-0.122	12.633	0,49236111
19	0.045	0.050	15.576	0,43194444
20	-0.179	-0.170	15.576	0,43194444
21	0.043	0.066	15.754	0,46805556
22	0.096	0,11944444	15.649	0,46944444
23	-0.049	-0.033	16.891	0,49861111
24	-0.075	-0.100	17.472	0,51180556

Based on the output above, most of the p-values are greater than 0.05, which means the model meets the requirements or there is no autocorrelation.

3. Heteroskedasticity Assumption

Table 10. Heteroskedasticity Correlogram

Lag	Autocorrelation (AC)	Partial Correlation (PAC)	Q-Stat	Prob
1	0,125	0,125	20.078	0,108333333
2	0.009	-0.024	20.125	0,254166667

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3	0.095	0,070138889	25.926	0,31875
4	0.045	0.010	27.258	0,420138889
5	-0.058	-0.068	29.534	0,490972222
6	0.029	0.047	30.106	0,561111111
7	-0.092	-0.120	35.948	0,572916667
8	-0.133	-0.087	48.499	0,536805556
9	-0.048	-0.014	50.139	0,578472222
10	-0.044	-0.030	51.552	0,611805556
11	-0.044	0.002	52.987	0,638194444
12	-0.114	-0.117	62.875	0,625
13	-0.088	-0.050	68.867	0,625
14	-0.093	-0.077	75.815	0,631944444
15	-0.064	-0.048	79.171	0,64375
16	-0.051	-0.036	81.327	0,65625
17	-0.035	-0.037	82.398	0,667361111
18	-0.047	-0.039	84.365	0,674305556
19	-0.036	-0.051	85.556	0,68125
20	0.063	0.056	89.250	0,683333333
21	0,129166667	0,104166667	10.184	0,649305556
22	-0.012	-0.104	12.198	0,666666667
23	0.064	0.066	12.611	0,672916667
24	0,106944444	0.075	15.059	0,638194444

The output shows that all p-values exceed 0.05, indicating the absence of heteroskedasticity problems. Thus, the model meets the non-heteroskedasticity criteria.

Safety Stock Calculation

The following explains how to calculate the safety stock value that minimizes stockouts while also reducing overall stockout costs, the risk of damage or obsolescence, and additional storage costs:

Safety Stock = SL × FE × √LT

where:

SL = Average Sales

FE = Forecast Error

LT = Product Lead Time

Based on the results of this study, the values obtained are:

SL = 33,11

FE = 4,043214

LT = 1 month

Safety Stock = 33,11 × 4,043214 × √30

= 733,24

The daily safety stock is 733,24/ 30 days = 24,44

By utilizing the data above, it can be concluded that this research object makes decisions, particularly regarding the inventory management of Ultra-Pure Water, which requires a

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minimum threshold of 24.44 units per day to ensure supply availability for the following month.

CONCLUSION

The research findings indicate that sales data are stationary and can be accurately modeled using ARIMA (1,0,1), which demonstrated the lowest Akaike Information Criterion (AIC) value and satisfied the assumptions of normality, with no signs of autocorrelation or heteroskedasticity. This model was then applied to sales forecasting and safety stock analysis.

The forecasting results provide an estimate of stable distribution requirements, with a safety stock value of 733.24 units per month or 24.44 units per day. This figure serves as an important reference in determining the minimum inventory threshold to prevent stockouts and ensure smooth distribution.

Thus, the application of Distribution Requirements Planning (DRP) combined with quantitative forecasting models such as ARIMA has proven effective in supporting distribution decision-making and inventory management. This research contributes to developing a more efficient and adaptive energy distribution strategy, particularly in the context of subsidized goods such as 3-kg LPG. In addition, this approach supports the achievement of the Sustainable Development Goals (SDG 9) by fostering innovation and efficiency in the national energy logistics system.

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