COMPARATIVE ANALYSIS OF ARIMA AND SUPPORT VECTOR REGRESSION FOR DEMAND FORECASTING AND SPARE PARTS MANAGEMENT IN COLD FLEET REPAIR AND MAINTENANCE

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Abstract. *This study presents a comparative analysis of ARIMA (Auto Regressive Integrated Moving Average) and Support Vector Regression (SVR) methodologies for demand forecasting and spare parts management in the context of cold fleet repair and maintenance operations. The efficacy of ARIMA modelling investigated through a comprehensive examination of spare parts demand at Hutama, a leading service provider in Indonesia, spanning from January 2019 to December 2023. Utilizing time series plotting, stationarity tests, and model selection criteria, ARIMA (0, 0, 1) is identified as the optimal forecasting model, providing valuable insights into projected spare parts usage. Concurrently, the study explores the effectiveness of SVR in accurately predicting spare part usage within the service and maintenance industry, focusing on coolers and freezers. Leveraging historical data from Hutama, the SVR model achieves remarkable precision through rigorous parameter tuning. Comparative analysis reveals differences in forecasting accuracy, with ARIMA demonstrating a MAPE (Mean Absolute Percentage Error) of 15.79% and RMSE (Root Mean Square Error) of 15.45, while SVR exhibits a MAPE of 10.10% and RMSE of 9.35. This comparative analysis contributes to enhancing spare parts management practices and operational efficiency in the service and maintenance industries.*

Keywords: *ARIMA, SVW, Comparative Analysis, Demand Forecasting*

1. INTRODUCTION

Forecasting plays a pivotal role in decision-making processes for both individuals and organizations, enabling the prediction of future events by analysing historical data within a defined timeframe. Time series forecasting, in particular, serves as a crucial method for predicting future values, aiding in planning and resource allocation (Alqatawna et al., 2023).

Various techniques exist for time series forecasting, catering to linear and non-linear data patterns. Linear data often utilize methods like Autoregressive (AR), Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving Average (SARIMA) models (Djoni, 2011; Ramos et al., 2014). In opposite side, non-linear data necessitates approaches such as Support Vector Machine (SVM), Backpropagation (BPG), K-Nearest Neighbours (KNN), and Fuzzy Time Series (FTS) (Kargul et al., 2017; Rais et al., 2022).

Among these various techniques, Autoregressive Integrated Moving Average (ARIMA) stands out as a robust model for capturing temporal dependencies in data, making it suitable for both linear and non-linear patterns. Its versatility and effectiveness demonstrated across various forecasting applications (Ramos et al., 2015). Support Vector Regression (SVR), an extension of Support Vector Machine (SVM) designed for regression tasks, offers a powerful tool for forecasting tasks, particularly for addressing non-linear data challenges. SVR effectively fits data while minimizing errors, showcase remarkable adaptability and performance (Kargul et al., 2017; Rais et al., 2022). Spare parts management within the service and maintenance industry presents unique challenges, including the need for accurate forecasting to ensure timely availability of parts for repairs and maintenance activities. In this study, we investigate the application of ARIMA and SVR methodologies for demand forecasting and spare parts management within the context of cold fleet repair and maintenance operations.

The cooler and freezer market in Indonesia is experiencing significant growth, driven by the expansion of the frozen food and beverage industry. Breakdowns in these essential appliances are frequent, emphasizing the importance of effective spare parts management to uphold functionality. This research leverages historical data from Hutama, a prominent service provider in Indonesia, spanning from January 2019 to December 2023. Specifically, we focus on forecasting spare parts demand related to cold fleet breakdowns, a critical aspect of Hutama's operations.

While ARIMA has been widely utilized in forecasting applications, its adaptation to spare parts demand forecasting in the service and maintenance industry remains underexplored. Similarly, the application of SVR for predicting spare parts usage dynamics in such contexts presents a notable gap in the existing literature.

This research aims to fill this gap by conducting a comparative analysis of ARIMA and SVR methodologies for demand forecasting and spare parts management. By addressing the specific challenges faced by companies like Hutama, we seek to enhance spare parts management practices, ultimately contributing to improved operational efficiency and service quality within the cold fleet repair and maintenance industry.

2. LITERATURE REVIEW

2.1 Forecasting Theory

Forecasting theory revolves around the notion that present and past knowledge and experiences can harnessed to make predictions about the future (Petropoulos et al., 2022; Syntetos et al., 2016). These predictions serve various purposes, from anticipating work requirements to predicting events like equipment failure, spare parts needs, or future weather conditions. As such, understanding the complexities of forecasting problems is crucial in developing effective theoretical frameworks. Theoretical insights gleaned from such analyses can then inform better practices, leading to more optimal outcomes (Armstrong & Green, 2018).

2.2 Concept of Spare Parts Demand Forecasting

Spare parts demand forecasting is a critical process that entails predicting the quantity and types of spare parts required within specific timeframes (İfraz et al., 2023; Pardede & Vanany, 2021; Van der Auweraer & Boute, 2019). Accurate forecasting in this domain is pivotal for successful spare parts inventory management, as it helps organizations avoid stock outs, downtime in repair work, and additional costs associated with emergency spare parts shipments. Effective spare parts demand forecasting relies on analyzing historical data, identifying demand trends, and considering external factors such as transportation and policy changes that can influence demand.

2.3 ARIMA Forecasting Method

ARIMA (Auto Regressive Integrated Moving Average) stands out as a robust method for demand forecasting, particularly in the context of time series and data analysis (İfraz et al., 2023). By modelling data as a combination of autoregressive, moving average, and differencing components, ARIMA effectively captures dependencies, patterns, and trends in historical data. While ARIMA has been widely utilized across various industries, its suitability for specific forecasting tasks requires careful consideration. Research suggests that incorporating demand indicators as exogenous variables into ARIMA models can enhance forecasting accuracy, particularly in supply chain contexts (Gonçalves et al., 2021).

ARIMA Model Equation:
$Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t$ --------------------------------------- (1)

Where:
M = constant.
$\phi_1, \ldots, \phi_p$ = the coefficient of the autoregressive parameter of order *p*.
$Y_{t=1}, \ldots, Y_{t-p}$ = Independent variable.
ε_t = residual at time *t*.

Differencing for stationarity:
$\Phi_p(B)\nabla^d Y_t = \xi + \Phi_q(B)\varepsilon_t$ -- (2)

Where:
Y_t = Observation value at time *t*
Φ_p = Autoregressive parameter
B = Backshift operator
d = Differencing parameter
ξ = Constant parameter
Φ_q = Moving average parameter
ε_t = Residual value (error)

2.4 SVR Forecasting Model

Support Vector Regression (SVR) emerges as a powerful tool for solving regression problems, including demand forecasting (Amanda et al., 2012; Yasin et al., 2014). SVR, a supervised learning algorithm, seeks to find a hyperplane that minimizes error while maximizing margin, effectively predicting continuous variable values. The method's adaptability to both linear and nonlinear data, coupled with its ability to address overfitting issues, makes it a valuable asset in forecasting spare parts demand. The selection of appropriate parameters, often optimized through methods like Grid Search, is crucial for maximizing SVR's predictive performance (Balasundaram & Prasad, 2020).

SVR Function Equation:
$f(x) = \langle w.x \rangle + b$ -- (3)

Where:
$f(x)$ = SVR Function
x = Input vector
w = Weight vector of dimension *l*
b = Bias

Optimization Problem:

Equation (3) is a general linear function, where ⟨.⟩ represents the dot product or scalar multiplication on x. To achieve good generalization of the function f(x), it done by minimizing w by solving the optimization problem as follows:

$min \frac{1}{2} \|w\|^2$ -- (4)

With the provision of:
$y_i - \langle w.x_i \rangle - b \leq \varepsilon$
$\langle w.x_i \rangle - y_i + b \leq \varepsilon$
ε = Margin

2.5 Model Evaluation

Evaluating forecasting models is essential for assessing their accuracy and reliability, guiding decision-making processes, and ensuring optimal model selection (Purwoko et al., 2023). Common evaluation metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) provide insights into the predictive performance of models. Lower RMSE and MAPE values indicate better accuracy, signaling the effectiveness of the forecasting model in spare parts inventory management. By selecting the most suitable forecasting model based on evaluation results, organizations can optimize spare parts stocking, reduce downtime, enhance efficiency, and mitigate additional costs associated with suboptimal forecasts.

The formula for RMSE is as follows:

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{(Z_t - \hat{Z}_t)^2}{n}} \text{ -- } (5)$$

Where:
Z_t = actual data at time *t*
$\hat{Z}_t$ = predicted data at time *t*
n = number of predicted data

The formula for MAPE is as follows:

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{Z_t - \hat{Z}_t}{Z_t} \right|}{n} \times 100\% \text{ -- } (6)$$

Where:
Z_t = actual data at time *t*
$\hat{Z}_t$ = predicted data at time *t*
n = number of predicted data

3. RESEARCH METHODS

3.1 Data Source

This research utilizes secondary data from Hutama, encompassing actual spare parts usage spanning from 2019 to the end of 2023. This dataset includes both hard copy and soft copy sources accessible to the company's top management.

3.2 Methodology for Comparison Analysis between ARIMA Model and SVR Model

To compare ARIMA and SVR models for demand forecasting and spare parts management, the data pre-processing ensures consistency across models by using the same dataset split into training and testing subsets. ARIMA undergoes differentiation to stabilize data variance, while SVR normalizes data for standardized scaling. Both models trained on the training dataset, with ARIMA parameters selected through analytical procedures and SVR parameters optimized via Grid Search Optimization.

Model Evaluation criteria include parameter significance, AIC minimization, residual characteristics using Ljung-Box test and normality assessment suing Saphiro-Wilk test. Metrics such as MAPE and RMSE quantify forecast accuracy, guiding the comparison between models. Statistical analysis, including confidence intervals, further validates model performance.

3.3 Comparison Analysis

Comparative analysis between ARIMA and SVR, using metrics MAPE and RMSE, highlights ability to predict spare parts demand. Integrating both models offers a comprehensive approach to demand forecasting and spare parts management, providing valuable insights for decision-making processes.

3.4 Forecasting

Following model selection, forecasting conducted using the chosen ARIMA model to estimate spare parts demand for six months beyond the available data. The research process follows a systematic approach, involving data collection, normalization, and analysis of spare parts usage trends. Parameters such as C and ε optimized, and model validation performed using testing data to project future trends and assess prediction accuracy through RMSE and MAPE calculations.

4. RESULT AND DISCUSSION

4.1 Results of ARIMA Model Testing

The following we present result and perform discussion for the Comparative Analysis of ARIMA and Support Vector Regression (SVR) for Demand Forecasting and Spare Parts Management in Cold Fleet Repair and Maintenance.

4.1.2 Data Stationarity and Model Identification

The analysis of spare parts usage data from January 2019 to December 2023 revealed significant fluctuations over the 60-month period, with an average utilization of 103 units spare parts. The stationary graph shown as follow:

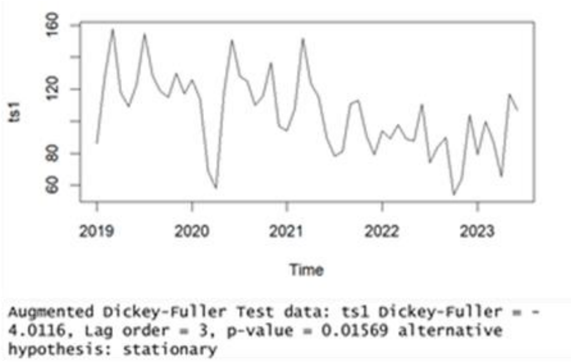

Figure 1. Stationarity Test Result

The results indicate that the data is stationary, so no additional differencing is necessary. Time series plotting and Augmented Dickey-Fuller Test confirmed the stationarity of the data, essential for ARIMA modelling, with a p-value of 0.01569.

The next step involves analyzing ACF and PACF plots to explore autocorrelation and partial autocorrelation.

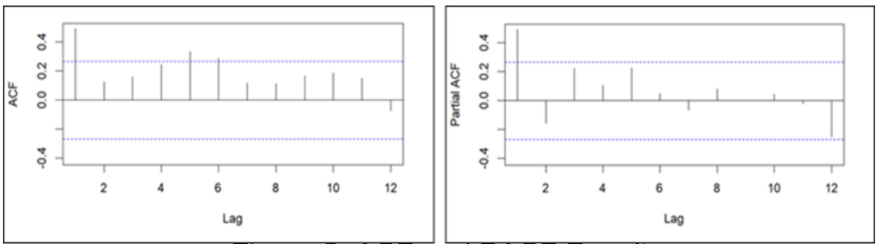

Figure 2. ACF and PACF Result

The ACF and PACF analysis indicates stationarity in the time series data at lag 1. Based on these findings, potential ARIMA models include ARIMA(1,0,1), ARIMA(1,0,0), and ARIMA(0,0,1). The parameter estimation results obtained using R software are as follows:

Table 1. Parameter Estimation Test Result

Model	**Significance**	**AIC**	**Ljung-Box test (White-Noise)**	**Saphiro-Wilk (normality test)**
ARIMA(1,0,1)	AR1=0,546 MA1=0,016 Int=0,000	485,81	0,983 (white)	0,755 (normal)
ARIMA(1,0,0)	AR1=0,000 Int=0,000	486,77	0,5339 (white)	0,4127 (normal)
ARIMA(0,0,1)	MA1=0,000 Int=0,000	484,18	0,7078 (white)	0,8096 (normal)

Based on the results shown in Table 1, the best model, ARIMA(0,0,1), is selected due to its smallest AIC value of 484.18. The forecast for spare parts usage over the next six months using this model is as follows:

Table 2. Forecasting Result Based on ARIMA Model

Month	**Spare part actual used**	**Forecasting result**
Jul 2023	109	97.07572
Aug 2023	92	104.6146
Sep 2023	80	104.6146
Oct 2023	109	104.6146
Nov 2023	92	104.6146
Dec 2023	86	104.6146

The forecasting results visualized in the following graph:

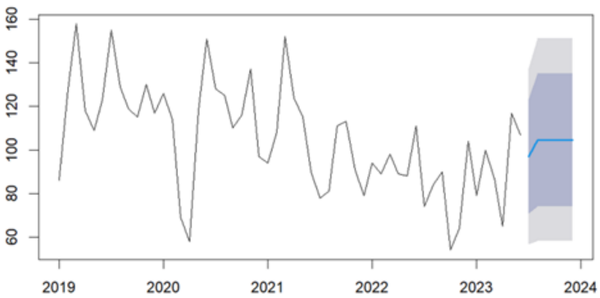

Figure 3. Forecasting Result Visualisation

Then the interpretation of the MAPE values based on the following table:

Table 3. MAPE interpretation

MAPE	**Interpretation**
<10	Highly accurate
10-20	Accurate
20-50	Reasonable
>50	Inaccurate

Source: (Fibriyani & Chamidah, 2020)

The model evaluation using MAPE and RMSE for the spare parts yielded a MAPE value of 15.79% and an RMSE value of 15.45. These evaluation results indicate that the ARIMA(0,0,1) model has an acceptable and accurate level of accuracy for forecasting spare part usage over the specified period.

4.2 Results of SVR Model Testing

The training data consists of 90% and the testing data 10%. The training data period is from January 2019 to December 2023. In SVR modelling, the response variable (Y) is spare parts, and the predictor variable (X) is the monthly period.

4.2.1 Results of SVR Model Testing

The first step before building an SVR model is to determine the data pattern to select the appropriate Kernel function. The data pattern can be linear or nonlinear, which is determined through the Terasvirta test. The Terasvirta test using R software for spare parts data yielded a p-value of 0.05353. This result indicates that the F-value of the Terasvirta test (df1 = 2, df2 = 57) is 3.0832. Since the p-value is greater than the significance level, we fail to reject H0, thus concluding that the spare parts data has a linear pattern. Therefore, the kernel function used in the SVR model is a linear kernel function.

4.2.2 Results of SVR Model Testing

After testing the data pattern with the Terasvirta test, the next step is to determine the lag that affects time t as a data variable. The determination of input lag based on the Partial Autocorrelation Function (PACF) plot. The PACF plot used to determine the partial correlation between variables in a time series considering a specific time lag. The PACF plot for SVR conducted to observe the dependency pattern between input and output variables in the time series. The determination of the influential lag based on the PACF plot presented in Figure 4.

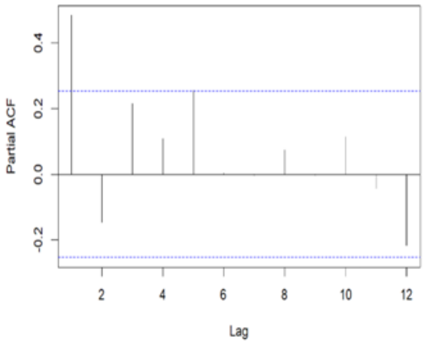

Figure 4. Determination of Influential Lag with PACF Plot

Based on the visualization in Figure 4, only the first lag is significantly influential, so the observations in the first time period not use. Therefore, in the SVR modelling, the training data starts from period t=2 to t=42, while the testing data starts from t=43 to t=60. This data use for SVR modelling.

4.2.3 Tuning SVR Parameters Using Grid Search Optimization

Based on the nonlinearity testing results, the SVR model used has a linear kernel with initial parameters Cost (C) and Epsilon (ε). To obtain the optimal parameters, the grid search optimization method is applied, which consists of two stages: the loose grid stage and the finer grid stage. The parameter value ranges for the loose grid stage presented in Table 4.

Table 4 Parameter Value Range for the Loose Grid

Parameter	**Value range**
Cost (C)	$2^1;\ 2^2; 2^3; \dots; 2^5;\ 2^6;\ 2^7$
Epsilon (ε)	$0;\ 0{,}01;\ \dots;\ 0{,}99;\ 1$

Table 4 shows the range of parameter values for the loose grid stage. The optimal results from the grid search method at this stage using R Software are Cost (C) = 2 and Epsilon (ε) = 0.7. Visualization of these results shown in the heat map in Figure 5.

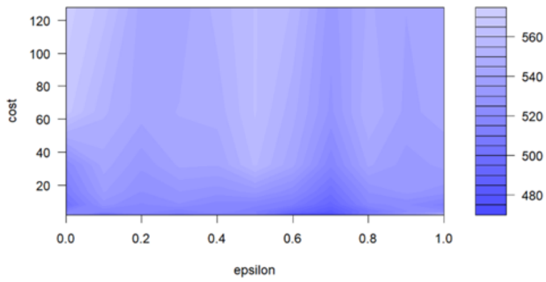

Figure 5. Heatmap Visualization Using Loose Grid Method

After obtaining the optimal parameters in the loose grid stage, the next step is parameter tuning with a finer grid. The finer grid stage aims to find the optimal values of Cost (C) and epsilon (ε) around the parameter values identified in the loose grid stage. The range of parameter values for the finer grid presented in Table 5.

Table 5. Parameter Value Range for the Finer Grid

Parameter	**Value range**
Cost (C)	$2^1; 2^{1,25}; \dots; 2^{1,75};\ 2^2$
Epsilon (ε)	$0;\ 0{,}01;\ \dots;\ 0{,}99;\ 1$

Based on Table 5, it shows the range of parameter values around the optimal parameter values obtained in the loose grid stage. These values then use to determine the optimal values for the finer grid stage.

In the finer grid stage, the selection of parameters C and epsilon is based on the results from the loose grid stage. The optimal range of parameter values for C and epsilon is around the values identified in the previous stage, selected based on the lowest error value. The optimal results from the finer grid are Cost (C) = 2 and Epsilon (ε) = 0.7. These parameters are used to determine the prediction accuracy of SVR. After tuning, the SVR model with the training data produces RMSE = 21.06 and MAPE = 17.02%, indicating good accuracy. Figure 6 shows that the SVR model with a linear kernel is effective for modelling spare parts usage trend.

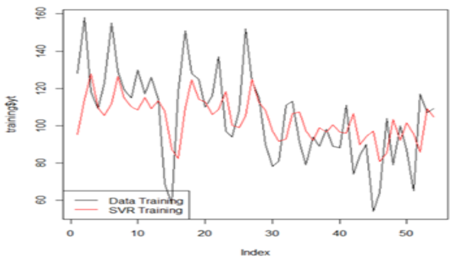

Figure 6. Prediction Plot of the SVR model after Tuning

4.2.4 Tuning SVR Parameters Using Grid Search Optimization

The SVR model with a linear kernel use to accurately predict spare parts demand. Predictions are made on testing data from t = 43 to t = 60, totalling 18 data points. The prediction results show an RMSE of 9.35 and MAPE of 10.10%, categorized as accurate. Visualization of the prediction results presented in Figure 25.

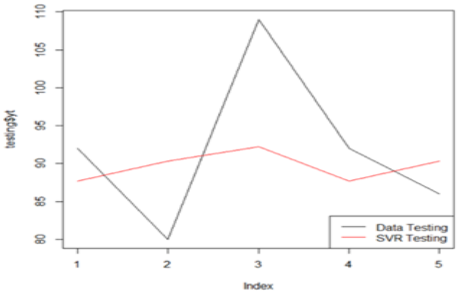

Figure 7. Prediction plot of the SVR model based on testing data

Based on Figure 7 and the values of RMSE and MAPE, the prediction results on the testing data indicate an accurate model for spare parts data.

4.2.5 Forecasting Results

The SVR model with a linear kernel use to accurately predict spare parts demand. Predictions are made on testing data from t = 43 to t = 60, totalling 18 data points. The prediction results show an RMSE of 9.35 and MAPE of 10.10%, categorized as accurate. Visualization of the prediction results presented in Figure 25.

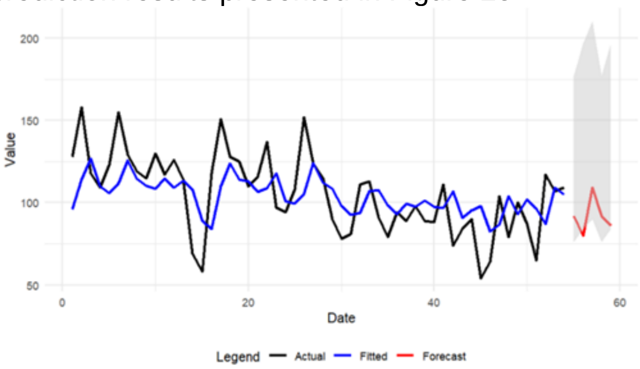

Figure 8. Forecasting Visualization Based on SVR Model

4.3 Comparison of ARIMA and SVR Model Results

Below is a summary of RMSE and MAPE results along with their interpretations for the forecasting models of ARIMA and SVR.

Table 6. RMSE and MAPE Comparison Result

Description	**ARIMA**			**SVR**		
	RMSE	MAPE	Interpretation	RMSE	MAPE	Interpretation
Spare part	15,45	15,79%	accurate	9,35	10,10%	accurate

4.4 Analysis and Comparison of Models

Based on the comparison between ARIMA and SVR models for demand forecasting and spare parts management in cold fleet repair and maintenance, several conclusions can be drawn. The SVR model exhibits lower RMSE and MAPE values compared to ARIMA, with RMSE of 9.35 versus 15.45 and MAPE of 10.10% versus 15.79%, indicating higher accuracy in predicting spare parts demand.

In terms of model training and tuning, ARIMA(0,0,1) was trained on historical data spanning from January 2019 to December 2023. It selected based on significance and diagnostic criteria, providing accurate forecasts for spare parts demand. On the other hand, SVR utilized the Terasvirta linearity test and grid search optimization (C=2, ε=0.4), demonstrating robust predictive capabilities for both linear and nonlinear data patterns.

In forecasting performance, ARIMA(0,0,1) provided accurate forecasts six months ahead, with MAPE and RMSE within the acceptable range of 10-20%, highlighting its precision in demand forecasting. Similarly, SVR achieved high accuracy in predicting spare parts, with minimal RMSE and MAPE values during testing, showcasing its robust forecasting capability.

Comparatively, ARIMA very good in capturing time series patterns and providing accurate forecasts for stable demand scenarios. Meanwhile, SVR's adaptability to nonlinear patterns enhances its forecasting effectiveness in dynamic environments. Integrating both models offers a comprehensive approach to demand forecasting and spare parts management, providing valuable insights for decision-making processes.

The study emphasize the importance of selecting the appropriate modeling approach based on data characteristics and forecasting requirements. It emphasizes the benefits of integrating ARIMA and SVR models to enhance forecasting accuracy and support effective spare parts management in cold fleet repair and maintenance operations.

CONCLUSIONS

This study conducted a comprehensive comparative analysis of ARIMA and Support Vector Regression (SVR) models for demand forecasting and spare parts management in cold fleet repair and maintenance. The research delved into the intricacies of each methodology, starting with data stationarity assessment and proceeding to model identification, parameter tuning, and forecasting.

The ARIMA model demonstrated its efficacy in capturing the dynamic nature of spare parts demand, leveraging time series analysis techniques to provide accurate forecasts. By identifying the optimal ARIMA model (0, 0, 1) through rigorous significance and diagnostic criteria evaluation, the study illustrated the model's ability to predict spare parts usage at Hutama. The ARIMA model's performance urther validated through metrics MAPE and RMSE, affirming its suitability for practical forecasting applications.

The SVR model shown its effectiveness in handling nonlinear relationships, particularly evident in spare parts exhibiting nonlinear patterns. Through Terasvirta testing and parameter tuning using grid search optimization, the SVR model accurately captured the complexities of spare parts data, yielding high accuracy in both training and testing phases. The SVR model's ability to adapt to varying data patterns highlights its versatility and potential for handling diverse forecasting challenges.

By comparing the strengths and limitations of ARIMA and SVR models, this study provides valuable insights into comparative performance in demand forecasting and spare parts management. While ARIMA very good in capturing linear relationships and stationary data, SVR offers robustness against nonlinearities and adapts well to diverse data patterns.

The implications of this comparative analysis extend beyond the field of cold fleet repair and maintenance, offering valuable guidance for decision-makers in various industries reliant on demand forecasting. By understanding the strengths and limitations of each methodology, organizations can make informed decisions regarding the selection and implementation of forecasting models, thereby optimizing spare parts management and enhancing operational efficiency.

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Author contributions

Conceptualization, ER, HS, MW; Methodology, ER, HS, MW; Software, ER; Validation, ER, ; Formal Analysis, ER; Investigation, ER; Resources, ER; Data Curation, ER; Writing-Original Draft Preparation, ER; Writing-Review & Editing, ER; Visualization, ER; Project Administration, ER; Funding Acquisition, ER.

Conflict of interest

The authors confirms that there is no conflict of interest with any parties involves with this research.

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