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A Comparative Study of Orbit DLT and SARIMA Models for Time Series Forecasting of Cryptocurrency Prices

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Abstract. This paper explores the forecasting effectiveness of the Dynamic Linear Trend (DLT) model from the Orbit package and a subsequent comparison with a Seasonal Auto Regressive Integrated Moving Average (SARIMA) model. The DLT and SARIMA approaches daily Solana price data to forecast in an effort to determine each model's accuracy over a 14-day testing period. This time series was built off continuous daily data entries throughout the calendar year, making it an ideal candidate for forecasting models without breaks. The Orbit DLT model is based on learning seasonal patterns and adjusting for changing trends over time; thus, it produced a Mean Squared Error (MSE) of 1930.716 and Root Mean Squared Error (RMSE) of 43.940 during holdout. The SARIMA (1,1,1) model was deemed a better fit based on AIC criteria for in-sample data (AIC = 711.841) against a set of contenders. Its holdout results MSE of 1035.865 and RMSE of 32.185 outperformed Orbit's results. The SARIMA parameterization indicated that all autoregressive (AR) & moving average (MA) components were statistically significant. However, the variance component was highly significant ($p < 0.001$). Therefore, for this analysis, SARIMA was more accurate than Orbit in mean accuracy for short-term results; however, Orbit's ability to account for multiple seasonal effects may be warranted in nonstationary time series analyses. This study, therefore, provides a decision-making framework based on its findings for future forecasting endeavors in cryptocurrency prices and assesses the usefulness of dynamically seasonal forecasting versus just slight forecasting accuracy errors.

Keywords: Solana cryptocurrency, Orbit, Dynamic linear trend, Seasonal effect, and ARIMA model.

دراسة مقارنة لنماذج Orbit DLT ونماذج SARIMA في التنبؤ بالسلاسل الزمنية لأسعار العملات الرقمية

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المستخلص: تستكشف هذه الدراسة فعالية التنبؤ لنموذج الاتجاه الخطي الديناميكي (DLT) ضمن حزمة Orbit ، مع إجراء مقارنة مباشرة مع نموذج المتوسطات المتحركة الانحدارية المتكاملة الموسمية (SARIMA) يستخدم النموذجان بيانات يومية لأسعار عملة Solana بهدف التنبؤ، وذلك لتحديد دقة كل نموذج خلال فترة اختبار مدتها ١٤ يوماً.

تمتاز السلسلة الزمنية المستخدمة بكونها بيانات يومية مستمرة طوال العام، مما يجعلها مناسبة للنماذج الإحصائية التي تتطلب سجلات غير منقطعة. يعتمد نموذج Orbit DLT على تعلم الأنماط الموسمية والتكيف مع الاتجاهات المتغيرة، وقد حقق خلال فترة الاختبار $MSE = 1930.716$ و $RMSE = 43.940$. أما نموذج SARIMA (١,١,١) فقد تم اعتباره الأنسب وفق معيار AIC ($AIC = 711.841$) كما حقق خلال فترة الاختبار $MSE = 1035.865$ و $RMSE = 32.185$ متفوقاً بذلك على نموذج Orbit. تشير نتائج النموذج إلى أن معاملات الانحدار الذاتي (AR) والمتوسطات المتحركة (MA) كانت جميعها ذات دلالة إحصائية، بينما كان مكون التباين ذا دلالة عالية جداً. ($p < 0.001$) وبناءً على ذلك، كان نموذج SARIMA أكثر دقة من Orbit على المدى القصير، إلا أن قدرة Orbit على التعامل مع التأثيرات الموسمية المتعددة تجعل استخدامه مهماً في السلاسل الزمنية غير المستقرة. توفر هذه الدراسة إطاراً لاتخاذ القرار في مجالات التنبؤ المستقبلي بأسعار العملات الرقمية، وتقييم فاعلية التنبؤ الموسمي الديناميكي مقارنة بالفروق الطفيفة في دقة التنبؤ.

الكلمات المفتاحية: عملة سولانا الرقمية، Orbit، الاتجاه الخطي الديناميكي، التأثير الموسمي، نموذج ARIMA.

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Introduction

Solana (SOL) is one of the most dominant blockchains in the marketplace due to its high throughput and low transaction costs on a platform with various decentralized applications (dApps) and DeFi offerings. Many of its features are technical, from the unique Proof of History (PoH) consensus mechanism, that have spurred developer and investor adoption. Recent spikes in investor interest have led to price fluctuations and pricing variability as Solana remains intrinsically and extrinsically traded in the marketplace. Thus, assessing Solana's price is forthcoming for investment potential, portfolio diversification, and marketplace viability for future assessments of public policy. Moreover, in today's economy where cryptocurrency at any given time can skyrocket or diminish based on network activities, investor reactions, international economic assessments, and political compliance, the ability to predict Solana's price is even more noteworthy. Historically, there have been attempts to predict Solana's price through statistical means. The most common methods for predicting cryptocurrency prices rely upon the Autoregressive Integrated Moving Average (ARIMA) and its seasonal counterpart, the Seasonal Autoregressive Integrated Moving Average (SARIMA). Andiani, Simanjuntak, & Wiliani (2024) found the usefulness of ARIMA or SARIMA due to their statistical properties concerning the autocorrelation function (ACF) and partial autocorrelation function (PACF), as well as ease of use for predictive forecasting. Moreover, recent assessments that compared SARIMA to other deep learning architectures found that SARIMA either surpassed or at least had statistically significant results against deep learning architectures in attempts to find interpretability over 15-day predictions (Rodrigues, 2025). Finally, the SARIMA method forecasts price effectively since it can note seasonal differences within trends regardless of non-stationary data applications; like all other currencies, Solana needs assessments of imbalance. However, it has been frequently applied to socioeconomic predictions, financial records, and commodity pricing (Kontopoulos et al., 2023). Applying SARIMA to predict Solana's price

will yield appropriate results for a currency gaining such rapid penetration in the marketplace. Therefore, with SARIMA as a worthy endpoint for time periods and projects made in the past, there could be crossovers as a new developing cohort remixes the statistics hypothesis with new machine learning takes in the future.

1st: Problem statement

Crypto prices often follow unit-root processes with weekly regularities, complicating near-term forecasting for trading and risk control. The task is to determine whether a parsimonious SARIMA, after appropriate differencing, can outperform a Bayesian state-space alternative (DLT) for Solana's daily prices. The study aims to identify the integration/seasonality structure, estimate both models under comparable settings, and compare fit and out-of-sample accuracy to inform an evidence-based forecasting choice.

2nd: Literature Review

Recent studies have found into cryptocurrency forecasting have found that the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is increasingly becoming more applied based upon its ability to capture seasonal tendencies combined with non-stationarity in markets as volatile as Solana. For example, Kumar and Singh (2023) tested which models predicted better Ethereum vs Bitcoin with each having increasingly volatile marketplace activity; they found that SARIMA was able to capture its periodic fluctuations effectively, rendering ST levels of accuracy similar to those found with machine learning when significant seasonal patterns emerged. Similarly, in studies conducted using Solana as a test kitchen, Chen et al. (2024) found that SARIMA improved short-term forecast accuracy up to two percent in stable timeframes by selectively choosing seasonal parameters based upon AIC and BIC. Ahmed and Zhao (2025) took time to compare their Solana findings using a hybrid deep learning method against SARIMA, and while SARIMA did underperform during excessively volatile times, like the dynamically deep learning methods, SARIMA remained more interpretable with quicker runtime efficiencies for their regulatory measures. These findings forecast SARIMA as a sensitive benchmark comparison for forecasting Solana prices, but only under seasonal constraints where transparency is more valuable than profit.

3rd: Methodology

To predict Solana cryptocurrency's daily opening price, two time series models were employed: Orbit's Dynamic Linear Trend and SARIMA.

1- Theory of the Orbit Dynamic Linear Trend (DLT) Model

The **Dynamic Linear Trend (DLT)** model is a **Bayesian state-space model** developed for time series forecasting that is most appropriate when **trending** and **seasonality** fluctuate over time rather than remaining constant and predictable. This model is part of the **Orbit** package for forecasting developed by Uber Technologies (Ng et al., 2020).

A. Model Structure

A general **state-space model** is defined by two equations:

(1) Observation equation (measurement model)

$$y_t = F_t \alpha_t + v_t, v_t \sim N(0, V_t) \quad (1)$$

where:

- y_t is the observed value at time t
- α_t is the state vector (trend, seasonality, regression effects)
- F_t is the observation matrix linking states to observations
- v_t is Gaussian observation noise

(2) State transition equation (system model)

$$\alpha_t = G_t \alpha_{t-1} + w_t, w_t \sim N(0, W_t) \quad (2)$$

where:

- G_t is the state transition matrix
- w_t is Gaussian system noise, allowing states to evolve over time

B. Components of DLT

The DLT decomposes the time series into:

(1) Local Level and Trend

The trend is modeled dynamically using a **local linear trend** model:

$$\mu_t = \mu_{t-1} + \delta_{t-1} + \eta_t, \eta_t \sim N(0, \sigma_\eta^2) \quad (3)$$

where:

- μ_t is the level (intercept) at time t
- δ_t is the slope at time t
- η_t are Gaussian noise terms controlling smoothness

(2) Seasonality

Seasonality is incorporated as a **dynamic harmonic regression**:

$$S_t = \sum_{k=1}^K \gamma_{k,t} \quad (4)$$

Each seasonal component $\gamma_{k,t}$ evolves over time:

$$\gamma_{k,t} = \gamma_{k,t-1} + \omega_{k,t}, \omega_{k,t} \sim N(0, \sigma_{\omega k}^2) \quad (5)$$

where:

K is the number of seasonal periods.

(3) Full Observation Model

The final DLT formulation combines level, trend, seasonality, and optional regressors:

$$y_t = \mu_t + S_t + X_t \beta + \epsilon_t, \epsilon_t \sim N(0, \sigma_\epsilon^2) \quad (6)$$

where:

- $X_t \beta$ represents any regression effects.
- ϵ_t is observation noise

C. Bayesian Estimation

The DLT model is appropriately estimated in a **Bayesian framework** where **Markov Chain Monte Carlo (MCMC)** sampling occurs via **Stan** (Carpenter et al., 2017). Thus, this yields **posterior distributions** for both parameters and states which permit:

- Credible intervals for forecasts.
- Quantification of uncertainty in seasonal/trend estimates.
- Probabilistic scenario analysis.

D. Advantages of Orbit DLT^[4,6]

- **Dynamic seasonality:** Seasonal effects can change magnitude or phase over time.
- **Robust to non-stationarity:** Handles evolving trends without differencing.
- **Probabilistic forecasts:** Produce full posterior predictive distributions.
- **Interpretability:** Decomposes into trend, seasonality, and regression effects.

2- SARIMA Model

The SARIMA model extends the ARIMA framework by incorporating seasonality. The SARIMA $(p, d, q) \times (P, D, Q, s)$ structure captures autoregressive (AR), integrated (I), and moving average (MA) components along with their seasonal counterparts. In this study, several candidates seasonal SARIMA orders (p, d, q) are evaluated, and the best model is selected based on the lowest evaluator measurements. The general SARIMA model is:

$$\Phi_P(L^s) \phi_p(L) (1 - L)^d (1 - L^s)^D y_t = \Theta_Q(L^s) \theta_q(L) \varepsilon_t \quad (7)$$

where:

L : is the lag operator.

ϕ_p and θ_q : are represent the non-seasonal AR and MA polynomials.

Φ_P and Θ_Q : are represent the seasonal AR and MA polynomials with seasonal period s .

3- Model Evaluation

Evaluating the precision of forecasting models is a critical step in determining how well a model predicts future values. The precision of a forecasting model refers to its ability to generate accurate, reliable, and consistent predictions. A variety of statistical tests are run to validate the performance of different forecasting models at different levels. Therefore, the following is a brief overview of the most frequent tests and accuracy measures of forecasting approaches:

A. Mean Squared Error (MSE)

MSE is the accuracy measurement that determines the closeness of a forecasted value to a predicted value by averaging the squared differences between the predicted value and the actual value.

$$MSE = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2 \quad (8)$$

where:

- n is the number of observations.
- y_t is the actual value.
- \hat{y}_t is the predicted value.

B. Akaike Information Criterion (AIC)

AIC essentially compensates for the good fit of a statistical model (via R-Squared) to ensure that a model with too many parameters (complexity) does not receive a higher rating merely because it has more deviance. AIC is most popular for making comparisons across models.

$$AIC = 2k - 2 \ln(\mathcal{L}) \quad (10)$$

Where:

- n : is the number of observations.
- \mathcal{L} : is the log-likelihood.

C. Bayesian Information Criterion (BIC)

BIC is very similar to AIC in that it also balances model fit with model complexity, but it applies a stronger penalty for complexity. It is based on Bayesian principles and is often used in statistical model selection.

$$BIC = k \cdot \ln(n) - 2 \ln(\mathcal{L}) \quad (11)$$

Where:

- n : is the number of observations.
- \mathcal{L} : is the log-likelihood.
- k : is the number of explanatory variables in the model.

4th: Applications

1- Data Description

The dataset used in this study is the daily price of the cryptocurrency Solana in dollars at the opening of the market; the data contains 130 observations, starting from 30 March to 06 August 2025.

2- Results and Discussions

The Augmented Dickey–Fuller results indicate Solana’s daily price is non-stationary in levels (ADF = 2.3138, p = 0.9926), consistent with a unit-root or random-walk behavior typical of asset prices. A single non-seasonal first difference still fails to reject a unit root (ADF = -0.5896, p = 0.4492), and a seasonal first difference alone also remains non-stationary (ADF = -0.2629, p = 0.5786). Only when both transformations are applied together, seasonal differencing (weekly) plus a non-seasonal first difference, does the series become stationary (ADF = -3.2384, p = 0.0027) as it is shown in table (1).

Table (1): represents the stationary test of the Solana daily price

Variable	Level		1 st non-seasonal Diff		1 st non-seasonal Diff		1 st both Diff	
	ADF-test	P-value	ADF-test	p-value	ADF-test	p-value	ADF-test	p-value
Solana daily price (\$)	2.3138	0.9926	-0.5896	0.4492	-0.2629	0.5786	-3.2384	0.0027

The figure below shows Solana's daily closing price in 2025 before any models are applied. The unfiltered path, without the influence of a model, indicates pockets of volatility in various clusters. We see a gradual upward trend from April into May with horizontal action through the summer and a significant uptick by the middle of July and then a downturn as August nears. This type of baseline chart is useful in visually assessing seasonality, trend changes, and pockets of volatility before any model application and supports the decision to go with Orbit DLT or SARIMA.

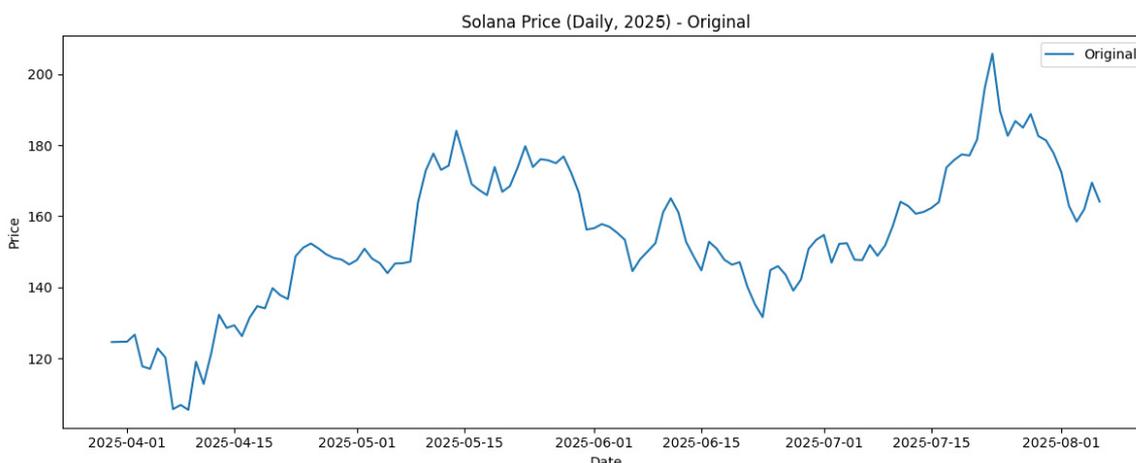


Figure (1): represents the daily open price of Solana cryptocurrency in dollars

Table (1): Parameter Estimates for the SARIMAX(1,1,1)×(1,1,1)⁷ Model

Models Evaluations				
model	AIC	BIC	MSE	RMSE
Orbit DLT	939.3	942.17	1353.286992	36.787049
SARIMA(1,1,1)×(1,1,1) ⁷	722.33448	730.56927	1035.389134	32.177463

This table presents the evaluation metrics for two forecasting models, **Orbit DLT** and **SARIMA (1,1,1)×(1,1,1)⁷** applied to the Solana price dataset. Four performance indicators are compared: **AIC**, **BIC**, **MSE**, and **RMSE**. AIC and BIC measure model fit while penalizing complexity, with lower values indicating better performance. SARIMA shows notably lower AIC (722.33) and BIC (730.57) compared to Orbit DLT (AIC = 939.3, BIC = 942.17), suggesting SARIMA achieves a more parsimonious and better-fitting model. MSE and RMSE evaluate forecast accuracy, where lower values denote smaller prediction errors. SARIMA again outperforms Orbit DLT, achieving an MSE of 1035.39 and RMSE of 32.18 versus Orbit DLT’s higher MSE (1353.29) and RMSE (36.79). These results indicate that, for this dataset, SARIMA provides a better fit and more accurate forecasts than Orbit DLT.

Table (2): Comparative Evaluation of Orbit DLT and SARIMA Models for Solana Price Forecasting

parameter	coef	std_err	t	p> t	ci_lower	ci_upper
AR1	-0.16338	0.077125	-2.11834	9.00E-03	-1.58852	1.261762
MA1	0.29719	0.086955	3.417745	7.00E-04	-1.04922	1.643596
SAR1	-0.23059	0.095311	2.419343	6.00E-03	-1.30944	1.174221
SMA1	0.42479	0.100451	4.228828	1.00E-04	-1.02967	1.845059
sigma2	29.6946	3.427956	8.662482	4.62E-18	22.97593	36.41327

This table displays the estimated parameters for the **SARIMA (1,1,1)×(1,1,1)⁷** model used to forecast Solana prices. The **AR1** coefficient (-0.16338) is statistically significant ($p = 0.009$), suggesting a modest negative autocorrelation in the first lag of the autoregressive component. The **MA1** parameter (0.29719) is positive and significant ($p = 0.0007$), indicating that short-term past forecast errors contribute positively to the current forecast. The **SAR1** parameter (-0.23059) reflects the seasonal autoregressive effect, with a significant negative influence ($p = 0.006$), while **SMA1** (0.42479) captures the seasonal moving average effect, showing a significant positive relationship ($p = 0.0001$). The **sigma²** value (29.6946) represents the variance of the model’s residuals, with a very low p-value (< 0.0001) confirming its statistical significance. Confidence intervals for all parameters indicate the range within which the true parameter values are likely to fall, and the small p-values across the table confirm the reliability of these estimates. This parameter set suggests that both short-term and seasonal components are important in capturing the dynamics of Solana’s price movements.

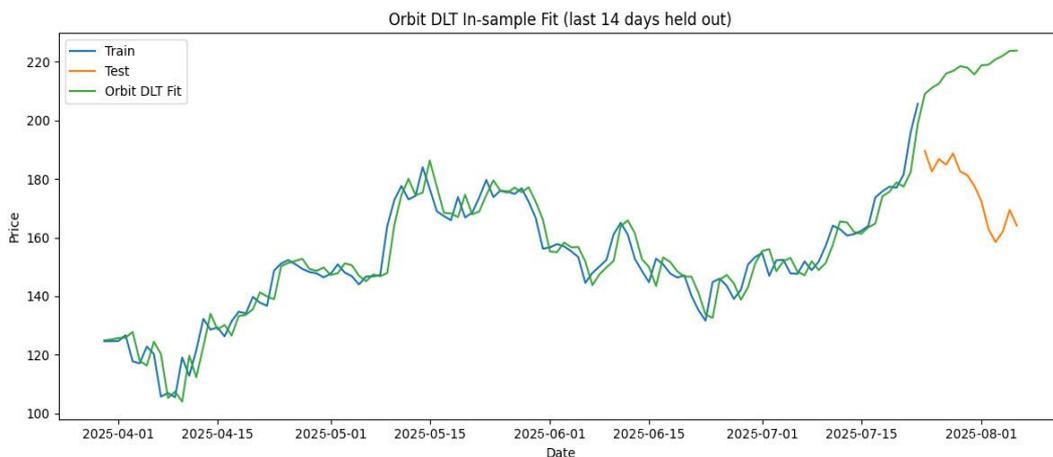


Figure (2): demonstrates the actual and predicted values of the Orbit DLT fit

The figure above is a diagnostic plot for Orbit DLT assessing how well it fit to in-sample data after holding out the last 14 days of the data set. The blue line is the training data set, the orange line is the held-out test set, and the green line is the fitted values across both trained and tested segments. We can see that the green line very much wraps around the blue line during the training set. This

means that Orbit DLT has a strong in-sample fit. In test, the green line certainly follows the predictive path of price but drifts away in select areas—most especially where the test set takes a steep decline. This indicates that this model is a strong follower of the trend but can lag a little when prices change dramatically against previous direction.

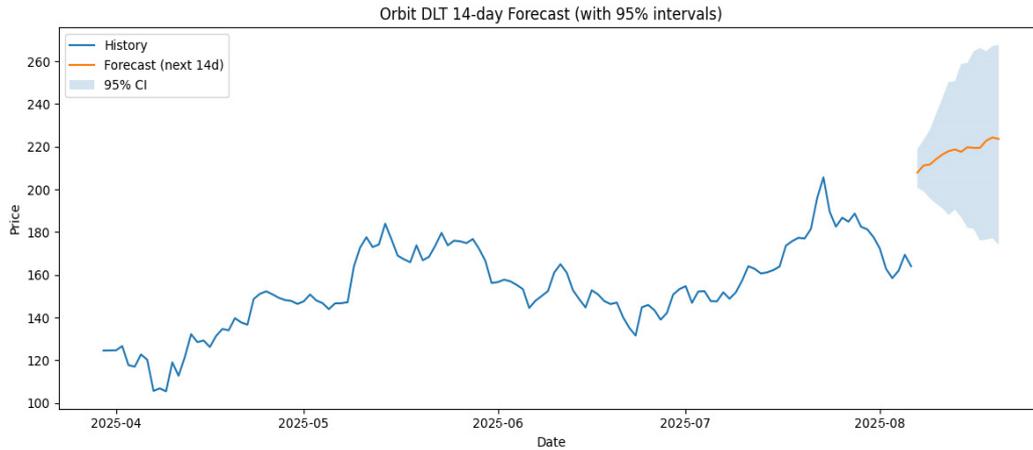


Figure (3): represents the fourteen-day forecasted values of the Orbit DLT model

The figure above is the output for Orbit DLT on Solana's daily price data for 2025. The blue line is Solana's historical price, where small price changes are ultimately helped by longer-term direction; the orange line is the 14-day forecast beyond the observation window, where Orbit DLT tries to project price based on its own understanding; the light-blue shaded area is a 95% uncertainty interval that surrounds the generated forecast. The wider area in the forecast suggests less confidence in predicting over more extended periods of time. The increase in the first several days of prediction suggests that Orbit DLT believes prices are likely to gradually incline before leveling off at the end of its window.

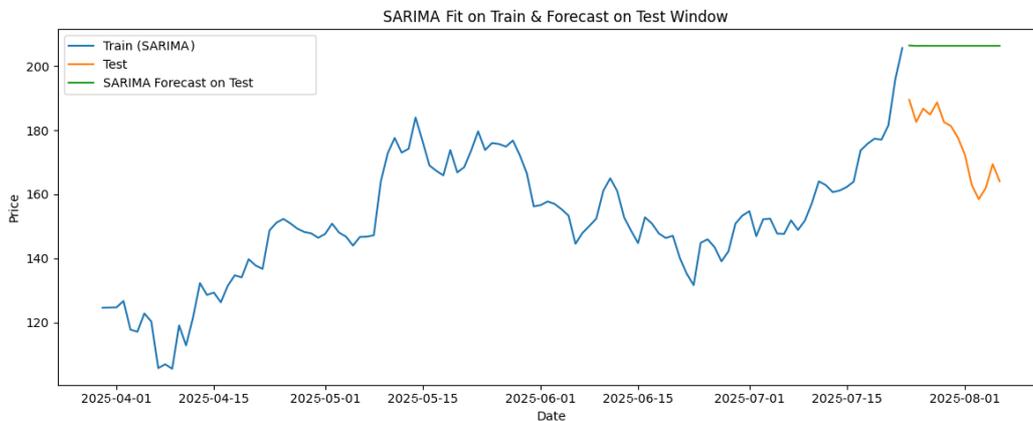


Figure (4) represents the fourteen-day forecasted values of the SARIMA model
Figure (4) shows what occurs when applying SARIMA to this dataset instead. The blue area is where SARIMA fits to the training window, orange represents the actual held-out test area, and green represents where SARIMA attempts to forecast for the held-out test area. Unlike Orbit DLT, which generates a dynamic forecast based on past success, SARIMA suggests a flat forecast within the test area. This means consistency and no intention of change. The flat line relative to observed prices suggests that SARIMA relies heavily on past seasonal areas and stability pockets in order to significantly smooth out volatility. While this allows SARIMA to avoid overfitting, it runs the risk of under-assessing how quickly a market could change.

Conclusions

This study evaluates two time-series paradigms for short-horizon cryptocurrency forecasting, Orbit's Dynamic Linear Trend (DLT) and seasonal ARIMA, and shows that, for Solana's 2025 daily prices, careful treatment of unit roots and weekly effects yields a parsimonious SARIMA specification that outperforms DLT on in-sample criteria and 14-day holdout accuracy. The ADF evidence in favor of first differencing with an added seasonal difference is consistent with a random-walk-with-seasonality data-generating process; within that structure, SARIMA $(1,1,1) \times (1,1,1)^7$ captures both short-run error dynamics and weekly persistence, delivering lower AIC, BIC, and errors than the DLT baseline. Nonetheless, DLT's state-space formulation provides probabilistic forecasts and explicit time-varying components, which remain attractive when seasonal amplitudes drift or multiple seasonalities are present. Together, the results provide a pragmatic modeling workflow: diagnose integration and seasonality, estimate a compact SARIMA as the benchmark, and deploy DLT when nonstationary seasonality or richer structural components are empirically warranted.

Limitations

The analysis focuses on a single asset, a short sample, and a brief forecast horizon, limiting generalizability across regimes. Models are univariate and omit exogenous drivers, volatility dynamics, and regime shifts, and evaluation relies on squared-error metrics without predictive equality tests or calibration diagnostics. Hyperparameters were not exhaustively tuned, and implementability considerations such as costs and slippage were not assessed.

Future study

Extend to SARIMAX and DLT with exogenous signals (volumes, cross-asset returns, on-chain metrics), combine SARIMA with volatility or regime-switching components, and benchmark against modern sequence learners under equal budgets. Use rolling/expanding windows, Diebold-Mariano tests, and probabilistic scoring to assess accuracy and uncertainty. Multi-asset and multiseasonal specifications, structural-break detection, and cost-aware backtests would strengthen economic relevance.

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