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Analysis of Trend and Seasonality in Live Streaming Sales and SARIMA Prediction Research

Jiaying Li*

Department of Engineering, Shenzhen MSU-BIT University, 1 International University Park Road, Shenzhen, China

**Corresponding author: Jiaying Li.*

Abstract

Sales forecasting serves as a cornerstone of modern e-commerce supply chain management, playing a pivotal role in inventory optimization and logistics planning. Diverging from traditional shelf-based models, livestreaming e-commerce is characterized by prominent "pulse-style" consumption patterns, featuring complex data dynamics and inherent seasonal fluctuations. Conventional simple moving average methods fail to capture such non-stationary volatility, often resulting in significant forecasting lag. Based on daily toy sales data from an e-commerce platform during 2022–2024, this study employs STL decomposition to extract long-term trends and weekly seasonality. It constructs a SARIMA $(1,1,1)\times(1,1,1)_7$ model for empirical prediction. The model achieved a Root Mean Square Error (RMSE) of 599.30 and a Mean Absolute Percentage Error (MAPE) of 21.46%. The results indicate that while SARIMA effectively captures the weekly periodicity in livestreaming sales, it exhibits limited capacity to predict "pulse effects" triggered by marketing campaigns. The research further investigates the impact of livestreaming interactions on model residuals, validating both the strengths and weaknesses of statistical models in identifying periodic regularities. Potential directions for future enhancements are also discussed.

Keywords

livestreaming e-commerce, time series analysis, SARIMA, trendiness, seasonality

1. Introduction

Sales forecasting plays a critical role in e-commerce operations, enabling firms to discern the underlying patterns of demand evolution. It serves as the foundation for mitigating "supply-demand mismatch" issues. Conventional forecasting methodologies largely depend on static historical averages, which are effective primarily in stable market conditions. However, within the evolving digital economy, livestreaming e-commerce has emerged as a novel engine for retail growth. According to Precedence Research [1], the global livestreaming e-commerce market is expanding at a compound annual growth rate of more than 30%. This paradigm significantly truncates consumer decision-making time through real-time interaction and visibility. It shifts the shopping paradigm from "search-based" (consumers seeking products) to "discovery-based" (products finding consumers) [2].

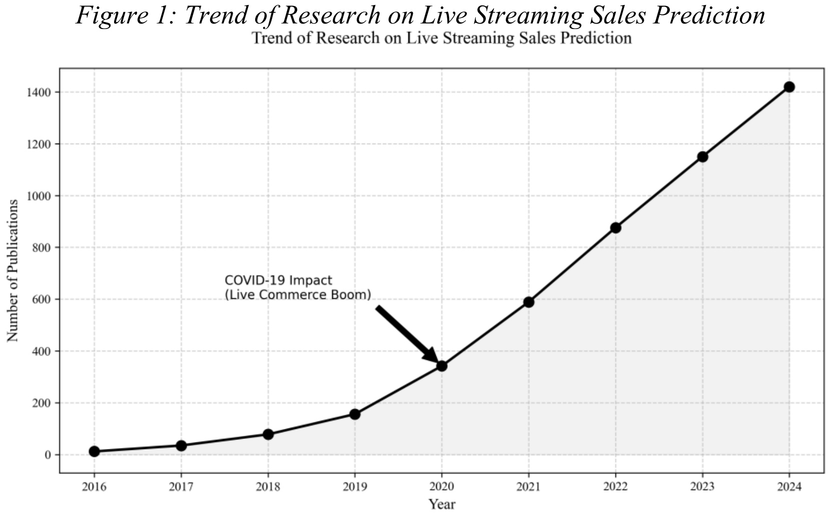
Nevertheless, the rapid proliferation of livestreaming e-commerce has exerted considerable strain on back-end supply chain operations, and in contrast to traditional retail, sales in livestreaming commerce exhibit heightened uncertainty and impulsiveness. For instance, a single livestreaming session by a leading influencer may precipitate drastic surges in order volume over a short timeframe. Such violent demand volatility is prone to exacerbate the “bullwhip effect” throughout the supply chain, forcing merchants into a dual predicament: the loss of customers due to stockouts versus excessive capital tied up in surplus inventory [3].

Precise sales forecasting is the key to addressing the challenges. However, industry understanding of livestreaming sales currently remains predominantly heuristic, lacking a rigorous quantitative analysis of intrinsic time-series characteristics (such as seasonality and long-term trends). Consequently, this study addresses the following core research questions: Do livestreaming sales exhibit statistically significant periodic regularities? Can the conventional SARIMA model effectively capture these underlying regularities to provide precise forecasts? Through empirical analysis, this research aims to reveal the operational dynamics of livestreaming data, thereby offering scientific insights for merchant scheduling and inventory preparation.

2. Literature Survey

Figure 1 illustrates the annual progression in the number of publications retrieved from the Web of Science and Google Scholar databases, using the keywords “live streaming e-commerce “and” sales forecasting”. (Search date: January 15, 2026; Document types: Journal articles and conference proceedings; Selection criteria: Non-English and irrelevant literature were excluded). Generally, the volume of related literature increased gradually from 2015, followed by a substantial surge after 2020, coinciding with the explosive growth of the livestreaming economy. This trend indicates a paradigm shift in academic focus, moving from qualitative explorations of “consumer behavior” toward “data-driven quantitative forecasting” research.

Figure 1: Trend of Research on Live Streaming Sales Prediction



2.1 Consumption Characteristics and the “PULSE Effect” in Livestreaming E-commerce

Previous studies posit that the fundamental distinction between livestreaming and traditional e-commerce lies in the cultivation of trust mechanisms and the creation of impulsive purchasing environments through real-time interaction. Drawing upon the lens of IT affordance, Sun et al. argue that the immediacy inherent in livestreaming significantly bolsters social presence, thereby fostering a sense of psychological immersion among consumers [4]. Zhen et al. further noted that this “sense of virtual togetherness” effectively bridges the psychological distance between the platform and the consumer, thereby facilitating rapid trust in the streamer [5].

Viewed through the lens of consumer behavior, purchasing actions during livestreaming sessions can be elucidated using the Stimulus-Organism-Response (S-O-R) framework [6]. Empirical research by Lee, C.-H. & Chen, C.-W. suggests that streamers’ linguistic cues and time-limited discounts function as external stimuli. These factors readily trigger emotional arousal in consumers, thereby directly precipitating impulsive purchasing intentions [7]. Dalal et al. noted that comprehensive product demonstrations, combined with real-time responsiveness, effectively capture consumer attention, thereby bolstering overall purchase intention [8]. Such behaviors manifest as instantaneous surges in sales within a time-series context, a phenomenon known as the “Pulse Effect”. Nevertheless, Lu and Chen caution that abrupt shifts induced by social interactions frequently lead to significant forecasting biases, which remain a primary factor contributing to the inadequacy of conventional forecasting models [9].

2.2 Evolution of Sales Forecasting Methodologies

In sales forecasting, a long-standing debate in academia persists over the comparative efficacy of statistical versus machine learning models. Makridakis et al., drawing on the M4 Competition results, noted that despite the significant attention garnered by pure machine learning approaches, statistical frameworks such as ARIMA maintain an indispensable level of robustness in certain specialized contexts [10]. Conversely, Xu et al. focused on the livestreaming context, identifying and analyzing critical variables that drive consumer purchasing behavior [11].

In recent years, deep learning algorithms have increasingly dominated the landscape of predictive modeling. A comprehensive review by Lim & Zohren highlights that Transformer and LSTM architectures exhibit superior performance in capturing long-range dependencies [12]. Kumar, Sunil, & Yadav explored a hybrid SARIMA-LSTM framework, demonstrating the efficacy of integrating linear and nonlinear methodologies [13]. While sophisticated models may yield superior precision, the hybrid modeling framework pioneered by Zhang and the conventional SARIMA model continue to serve as pivotal tools for constructing inventory baselines in industrial settings, owing to their computational efficiency and the clear physical significance of their parameters (such as the seasonal period s) [14].

2.3 Limitations of Existing Research and the Scope of This Study

In summary, while extant literature has made significant strides across the twin dimensions of consumer behavior and sales forecasting methodologies within the livestreaming ecosystem, several salient limitations nevertheless persist, as detailed below:

First, there is a significant gap between consumer behavior theories and quantitative forecasting methodologies. While research grounded in S-O-R theory and IT affordance perspectives has profoundly elucidated the psychological triggers of impulse purchasing in livestreaming contexts [9], they remain largely confined to qualitative assessments or cross-sectional survey data, failing to operationalize the “pulse effect” into quantifiable time-series characteristics. To put it differently, extant literature addresses the causality of pulses (“why they occur”) but leaves the spatio-temporal distribution and predictability of these spikes unaddressed.

Second, current predictive models lack adequate fitness for the idiosyncratic nature of livestreaming contexts. While models like SARIMA and LSTM have proven effective across diverse domains [10, 12], most conventional benchmarks—including traditional retail, power loads, and traffic flow—feature relatively smooth data trajectories. Conversely, livestreaming sales data exhibit a dual-component structure: long-term stationarity coupled with short-term stochastic pulses. Traditional statistical models assume that residuals follow a normal distribution with a mean of zero, which makes it difficult to capture extreme pulses triggered by marketing stimuli. Conventional statistical frameworks (such as ARIMA) assume that residuals are normally distributed with zero mean, which struggles to accommodate the leptokurtic spikes (extreme pulses) induced by marketing stimuli. Although pure machine learning models excel at fitting non-linear relationships, they typically necessitate exhaustive feature engineering; furthermore, they are frequently susceptible to overfitting during out-of-sample forecasting [16].

Third, there is a lack of a decoupled modeling strategy that distinguishes “baseline sales” from “pulse increments”. Prevailing hybrid frameworks, such as SARIMA-LSTM, typically treat the entire sales series as a monolithic entity for model fitting [17]. These approaches fail to account for the intrinsic divergence in the underlying generative mechanisms between predictable periodic baselines and stochastic marketing-driven pulses. Such a monolithic modeling paradigm not only risks compromising the fitting accuracy of periodic patterns due to the interference of sporadic pulses but also falls short of providing actionable insights for multi-echelon inventory strategies in supply chain management [18].

To address the limitations, this study adopts a "divide-and-conquer" analytical framework, initially leveraging STL decomposition and the SARIMA model to isolate and predict the "baseline water level"—namely, the periodic and trend-driven components—of livestreaming sales. Subsequently, the research conducts a dedicated analysis of the "pulse effect" embedded within the residual terms, characterizing its distribution and quantifying its impact on overall forecasting inaccuracies. This research trajectory simultaneously exploits the advantages of statistical models for capturing linear periodic regularities while explicitly delineating their operational boundaries, thereby establishing a precise problem formulation for subsequent integration of exogenous covariates or hybrid modeling architectures.

3. Data and Methodology

3.1 Data Sources and Preprocessing

Data for this research were extracted from the administrative interface of a leading e-commerce platform, utilizing daily sales records of the "Toys" category spanning 2022 to 2024 as the primary observational dataset. The selection of the toy category is predicated on its pronounced emotional consumption traits and the target audience's heightened sensitivity to interactive environments, rendering it an ideal proxy for validating the S-O-R framework and the resulting "pulse effects".

The data preprocessing procedure is executed in three stages: first, filtering the dataset to isolate sales records within the "Toys" category; second, aggregating these records daily; and third, performing missing value imputation to derive a comprehensive daily sales sequence Y_t. It should be noted that sales on non-streaming days were imputed as zeros, a choice justified by the strong dependence of sales on active sessions; since negligible transactions occur during off-stream periods, these zeros reflect the operational reality rather than a lack of data. Supplementing such entries with techniques such as linear interpolation risked generating "artificial sales" for non-streaming intervals, which would skew the raw data distribution and undermine the integrity of pulse-effect characteristics; hence, preserving original zeros remains the most robust methodological approach for this research.

Descriptive statistics for the sampled data reveal a total observation horizon of 731 days (January 1, 2022, to January 1, 2024), yielding a mean daily sales volume of 573.2 units alongside a standard deviation of 362. 1 units, with a skewness of 0.87 (the distribution is positively skewed, reflecting a predominance of low-sales days punctuated by infrequent high-volume peaks); furthermore, a kurtosis of 0.46 indicates a leptokurtic tendency relative to a normal distribution, signifying a non-negligible probability of extreme values. Taken together, these statistical attributes further substantiate the "pulse-like" nature inherent in livestreaming sales dynamics.

3.2 STL Time-Series Decomposition

To ascertain the presence of latent statistical regularities in livestreaming sales, the raw series was decomposed using the STL (Seasonal-Trend decomposition using Loess) algorithm into trend (T_t), seasonal (S_t), and remainder (R_t) components, as presented in Figure 2. The decomposition reveals three primary insights:

First, the trend component shows an upward trajectory, indicating the progressive expansion and maturation of the brand's follower base.

Second, the seasonal component reveals a robust "weekly seasonality" pattern, with peaks predominantly clustering between Friday and Sunday, a pattern highly congruent with consumer behavioral rhythms during leisure time.

Third, regarding the remaining component, distinct extreme values persist even after trend and seasonal filtering, effectively capturing the "pulse-like" purchasing behavior induced by marketing stimuli.

Figure 2: STL decomposition results for toy category livestreaming sales (Trend, Seasonal, and Remainder components)

3.3 Sarima Model Specification and Development

Given the pronounced seasonal characteristics identified via STL decomposition, conventional ARIMA models prove inadequate for capturing the data's complexity. Consequently, this study adopts a SARIMA $(p,d,q)\times(P,D,Q)_s$ framework for forecasting, specifying a seasonal periodicity of s=7 to reflect the weekly operational cycle. Simultaneously, first-order non-seasonal (d=1) and seasonal (D=1) differencing are employed to mitigate non-stationarity, thereby enhancing the model's ability to characterize the underlying volatility of livestreaming sales under baseline conditions.

3.3.1 Stationarity Diagnostics and Identification of Differencing Orders

An Augmented Dickey-Fuller (ADF) test was performed to examine the presence of a unit root in the raw time series. Results indicate that the ADF statistic for the original series Y_t is -2.843, with a corresponding p-value of 0.052. At the 0.05 significance level, the test fails to reject the null hypothesis of a unit root, thereby confirming the non-stationarity of the original series.

To mitigate the observed trend, first-order non-seasonal differencing was applied, defined as $\nabla Y_t = Y_t - Y_{t-1}$. Re-evaluating the transformed series using the ADF test yielded a statistic of -12.471 ($p < 0.001$), providing strong evidence against the unit root hypothesis and confirming stationarity. Consequently, the non-seasonal integration order for the model is specified as d=1.

Given the evident weekly seasonality, the raw series was subjected to first-order seasonal differencing, expressed as $\nabla_7 Y_t = Y_t - Y_{t-7}$. ADF test diagnostics yielded a statistic of -8.926 ($p < 0.001$), confirming that seasonal differencing effectively achieved stationarity. To ensure the comprehensive mitigation of non-stationarity, dual differencing (both non-seasonal and seasonal) was expressed as $\nabla\nabla_7 Y_t$, producing a highly significant ADF statistic of -15.238 ($p < 0.001$). Consequently, the seasonal integration order for the model is established as D=1.

3.3.2 Identification of Model Orders and Lag Structure

Following the specification of d=1, D=1, and s=7, the next step involves identifying the non-seasonal autoregressive (AR) order p and moving average (MA) order q. Concurrently, the seasonal autoregressive order P and the seasonal moving-average order Q must be determined. The identification process is predicated on the truncation (cutting-off) and decaying (tailing-off) properties observed in the ACF and PACF correlograms of the differenced series [19].

For the non-seasonal component, ACF and PACF correlograms (up to 40 lags) were generated for the series subjected to both trend and seasonal differencing. Inspection of the non-seasonal lags (1-6) reveals that the ACF coefficient at lag 1 is significantly non-zero, followed by a steady exponential decay—a characteristic “tailing-off” pattern. According to the Box-Jenkins methodology, the decaying nature of the ACF suggests the inclusion of a Moving Average (MA) term, leading to an initial specification of q=1; Correspondingly, the PACF exhibits a significant spike at lag 1, but truncates sharply after lag 2, remaining within the 95% confidence bounds, thus demonstrating a “cutting-off” behavior.

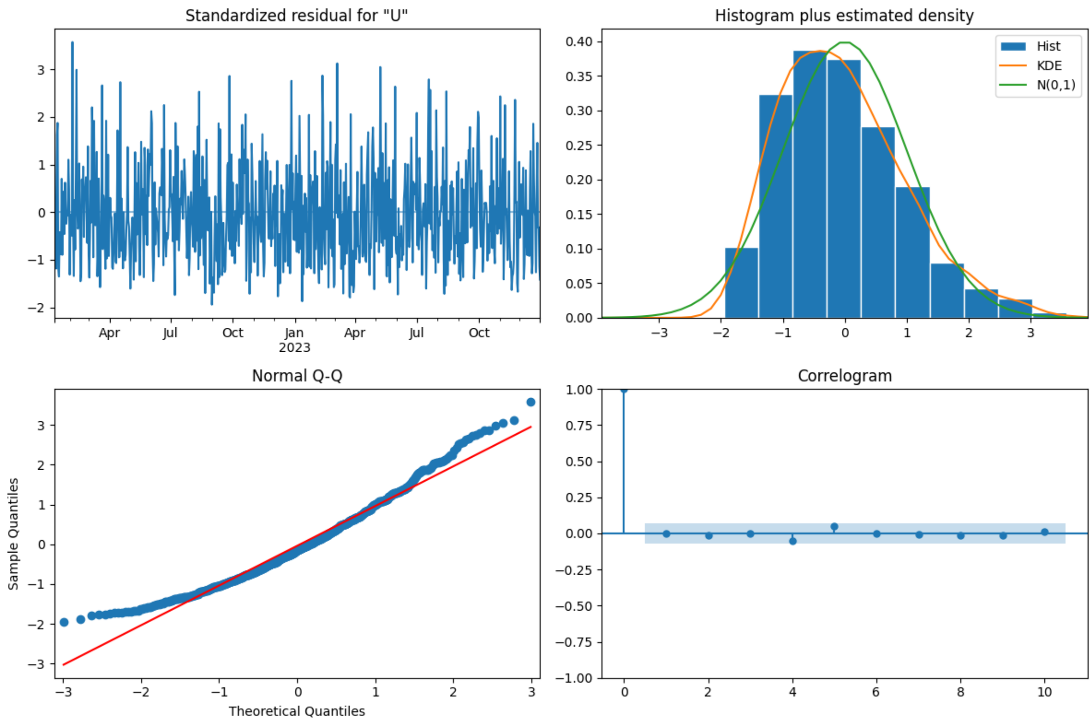
Regarding the seasonal components, the ACF and PACF correlograms were examined specifically at seasonal multiples (lags 7, 14, 21, and 28). It is observed that the ACF exhibits a significant spike at lag 7, followed by a gradual decay from lag 14 onwards, manifesting a seasonal “tailing-off” pattern that suggests an initial Q=1. Conversely, the PACF displays a significant partial autocorrelation at lag 7 but truncates sharply from lag 14, demonstrating a seasonal “cutting-off” (truncation) characteristic, which points to P=1.

In light of the above analysis, the SARIMA $(1,1,1)\times(1,1,1)_7$ architecture is tentatively identified as the primary candidate model.

3.3.3 Model Diagnostics and Residual Analysis

To ensure that the specified SARIMA $(1,1,1)\times(1,1,1)_7$ model has comprehensively captured the underlying dependency structures within the time series, a rigorous diagnostic suite is applied to the model residuals. Figure 3 illustrates the diagnostic profile of the model residuals, comprising four distinct subplots: the standardized residual time series, the residual histogram superimposed with a kernel density estimate, the Normal Quantile-Quantile (Q-Q) plot, and the residual Autocorrelation Function (ACF) correlogram.

Figure 3: Diagnostic plots for the SARIMA (1,1,1)×(1,1,1)7 model residuals



The standardized residual plot (top-left) reveals that the residuals fluctuate randomly around the zero baseline, exhibiting no discernible trends or volatility clustering. This suggests that the series' primary dynamics have been effectively captured. Despite several outliers exceeding the ±2 threshold—reflecting “impulse effects” triggered by marketing activities that the structural model fails to capture—the residual series remains overall stationary. In the normal Q-Q plot (bottom-left), the observations align closely with the 45-degree reference line, signifying that the residuals are approximately normally distributed; This is further corroborated by the histogram and kernel density estimate (top-right), which display a generally symmetric distribution of residuals; The residual ACF correlogram (bottom-right) illustrates that the autocorrelation coefficients across all lags remain within the 95% confidence bounds, confirming the absence of serial correlation and verifying that the residuals constitute a white noise process.

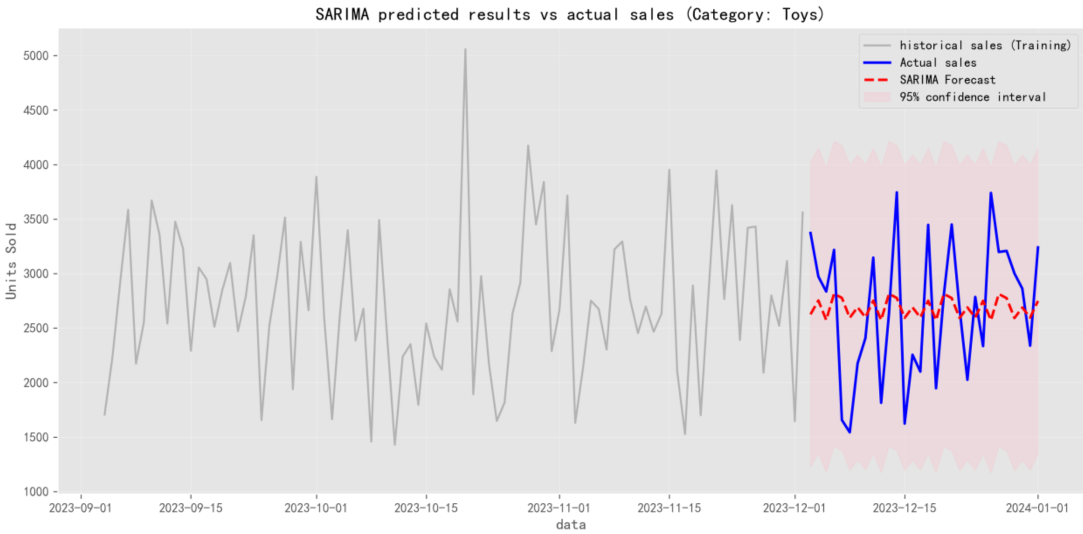
Integrating the diagnostic findings, the residuals of the SARIMA $(1,1,1)\times(1,1,1)_7$ model demonstrate the properties of a white noise process, indicating that the model is well-specified and provides a robust foundation for subsequent forecasting.

4. Empirical Analysis and Discussion

4.1 Assessment of Forecasting Performance

Utilizing the established SARIMA framework, a 30-day out-of-sample forecast was conducted. The alignment between the predicted trajectories and observed data is illustrated in Figure 4. Visual inspection reveals that the SARIMA model effectively replicates the oscillatory rhythm of sales volume. Specifically, the model demonstrates high fidelity in pinpointing weekly cyclical peaks and troughs, as evidenced by the synchronized fluctuation frequencies between the predicted (red) and actual (blue) series. This validates that under steady-state operations, absent major promotional shocks, livestream sales follow a predictable pattern characterized by distinct statistical periodicity.

Figure 4: Comparison between SARIMA model predictions and actual sales volume (with 95% confidence intervals)



4.2 Residual Diagnostics and the Challenge of "Impulse Shocks"

To provide a quantitative assessment of the model's predictive fidelity, the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were computed. Empirical findings yield an RMSE of 599.30 and a MAPE of 21.46%, providing a benchmark for the model's accuracy.

While the model effectively captures the weekly oscillatory patterns of sales, the MAPE metric suggests persistent discrepancies in predictive accuracy. Visual inspection of Figure 4 reveals that the observed sales (blue line) exhibit pronounced spikes at specific temporal nodes. In contrast, the predicted series (red line) tracks the upward trend, but its amplitude is significantly lower than in the empirical observations. This phenomenon corroborates the theory proposed by Zhang et al., which asserts that exogenous variables, such as influencer vocal cues or flash-sale prompts, frequently catalyze sales surges in livestreaming e-commerce. As an endogenous framework, SARIMA relies exclusively on historical lag structures and is inherently insensitive to real-time marketing stimuli within the livestream environment. Consequently, the model exhibits significant temporal lagging and systematic underestimation at these "impulse points" [16].

4.3 Future Research Directions

To overcome the inherent constraints of linear frameworks in capturing "impulse shocks", subsequent research may pursue breakthroughs along the following trajectories:

First, the integration of exogenous covariates via the ARIMAX (AutoRegressive Integrated Moving Average with Explanatory variables) framework. Drawing on the methodology proposed by Tridalestari et al. Such an approach is poised to significantly enhance the model's sensitivity and predictive accuracy regarding sales spikes [20].

Second, the adoption of a hybrid machine learning integration strategy. Drawing on nonlinear architectures such as Long Short-Term Memory (LSTM) networks or Random Forests can be used to model residual components [21]. By constructing a synergistic "SARIMA-ML" hybrid forecasting framework, the model can simultaneously capture the linear periodicities and the stochastic, nonlinear "burst" dynamics inherent in sales data.

5. Conclusion and Future Directions

Based on an empirical analysis of livestream sales data within the toy category, this study yields the following insights:

First, livestream e-commerce is not a purely stochastic process; its baseline traffic demonstrates pronounced weekly seasonality, as robustly evidenced by the STL decomposition analysis (Fig. 2).

Second, linear statistical models possess inherent structural boundaries. The SARIMA framework is well-suited for estimating the "baseline sales volume", offering a reliable benchmark for steady-state inventory management. However, when confronted with impulsive consumption surges driven by the S-O-R (Stimulus-Organism-Response) mechanism, univariate linear models face inherent constraints.

Building upon these findings, we propose a "Layered Inventory Strategy" [22] for practitioners, structured across two distinct dimensions:

The primary layer is Base Inventory. Stocking levels should be calibrated using the normative sales volume forecasted by the SARIMA model to secure supply during routine periods and mitigate the risk of overstocking.

The secondary layer is Elastic Inventory. To address the "impulse spikes" that elude the algorithmic capture in Figure 3, merchants must look beyond pure statistical modeling. They should integrate internal marketing calendars to develop "safety stock" protocols, or establish Quick Response (QR) pipelines with upstream suppliers to buffer against exogenous, abrupt demand shocks.

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Conflicts of Interest

The authors declare no conflict of interest.

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