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A Commodity Demand Forecasting System Based on Dual-Phase Conditional Diffusion Model

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ABSTRACT

Accurate demand forecasting enables efficient supply chain management. However, two major challenges persist: (a) insufficient modeling of external conditional variables and poor capture of complex multimodal demand distributions and (b) conditional information that is fused only once at the system input, causing information decay and reduced responsiveness to event-driven shocks. To this end, the authors propose a dual-phase conditional diffusion model (DP-CDM) in which a reverse sliding diffusion along the temporal axis exploits temporal continuity to build an autoregressive mechanism, enhancing sequence modeling and avoiding structural misalignment. In addition, noise-degradation diffusion enriches multimodal probabilistic representations and improves robustness to external disturbances. A conditional embedding module aligns multimodal features by aggregating local histories, global trends, and SHapley Additive exPlanations (SHAP)-quantified external factors, which are injected throughout the denoising processes. A 3.7% improvement in fitting performance showed the effectiveness of this model in capturing event-driven demand dynamics.

KEYWORDS

Deep Learning, Demand Forecasting, Supply Chain, Time Series, Inventory Optimization

INTRODUCTION

The digital transformation of supply chains has profoundly reshaped the way enterprises manage production, inventory, and logistics (Douaioui et al., 2024; Ghobakhloo et al., 2025; X. Zhu et al., 2024). Central to this transformation is demand forecasting, which serves as the foundation for responsive decision-making in procurement, production scheduling, and distribution planning. Accurate forecasts not only mitigate risks of overstocking or stockouts but also enable supply chains to operate with greater resilience and efficiency (Bouazizi et al., 2024; Kagalwala et al., 2025). As global supply chains become increasingly dynamic and complex, the development of advanced demand forecasting methods has emerged as a pressing research priority in both academia and industry.

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Recent years have witnessed significant advances in data-driven demand forecasting. Traditional statistical approaches, such as linear regression (Kong et al., 2025) and autoregressive models (Salinas et al., 2020), provide interpretability but often struggle to capture nonlinear dependencies and irregular demand fluctuations. More recent machine learning and deep learning methods, including recurrent neural networks (RNNs; Khaldi et al., 2023; Nejadettehad et al., 2020), convolutional architectures (Jiang et al., 2023; Zhang & Chen, 2025), and attention-based transformers (Oliveira & Ramos, 2024; Zhang et al., 2024), have significantly improved forecasting accuracy by modeling sequential dependencies and incorporating exogenous features.

Despite these advances, several persistent challenges remain. These challenges limit the effective modeling of the influence of external conditional factors, such as promotions, economic indicators, and disruptions, which play a decisive role in shaping demand. Moreover, although advanced generative models (Jinka et al., 2025; Ma et al., 2026) have demonstrated the ability to capture probabilistic distributions, they typically fall short in representing the inherently multimodal and event-driven nature of real-world demand. Finally, most existing approaches integrate conditional information only once at the model entrance, leading to the fading of information as signals propagate through deep layers. This reduces sensitivity to event-driven demand shocks, which are particularly critical for digital supply chain operations. These gaps call for the design of a new modeling paradigm that is capable of aligning external drivers with temporal structures and maintaining consistent conditional guidance throughout the forecasting process.

To address these challenges, we propose a dual-phase conditional diffusion model (DP-CDM) for demand forecasting in digital supply chains. Our approach is built around a dual-diffusion mechanism and a novel conditional embedding strategy. In the first phase of the model, a reverse sliding diffusion along the temporal axis establishes a supervised autoregressive reconstruction mechanism, strengthening temporal continuity and ensuring structural alignment of predictions. In the second phase, a noise-degradation diffusion enhances the model's ability to capture multimodal probabilistic distributions while improving robustness against exogenous disturbances. To complement this, we designed a conditional embedding module with multimodal feature alignment (CEM-MFA), which integrates global trends, local historical windows, and SHapley Additive exPlanations (SHAP)-quantified external features into a unified embedding space. Unlike conventional one-shot conditioning, these multimodal embeddings are injected consistently throughout both denoising phases, ensuring persistent alignment between external drivers and temporal dynamics. In the present study, extensive experiments on benchmark datasets demonstrated that DP-CDM not only captures event-driven dynamics more effectively but also achieves substantial improvements over state-of-the-art baselines. Compared with the strongest baseline, DP-CDM consistently achieved statistically significant improvements across datasets and forecasting horizons. On the Corporación Favorita Grocery Sales dataset, DP-CDM reduced the mean absolute percentage error (MAPE) by 1.8% for 20-day-ahead forecasting while improving R^2 by up to 3.7 percentage points. The contributions of this work can be summarized as follows:

- A novel dual-phase conditional diffusion framework for demand forecasting in digital supply chains, which enables accurate predictions under event-driven dynamics, is proposed.
- We designed a dual-phase generative diffusion module that combines autoregressive sliding diffusion with noise-degradation diffusion, thereby enhancing temporal continuity, preserving structural alignment, and improving robustness to exogenous noise.
- We developed a conditional embedding module, based on multimodal feature alignment, that aggregates multimodal conditions into a unified embedding space and injects them consistently across both denoising phases, ensuring persistent alignment between external drivers and temporal dynamics.

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