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Original Article

Reducing Overstock in Hospitality Lighting Inventory with Data Forecasting

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Abstract: *In the hospitality lighting sector, managing inventory efficiently remains a persistent challenge. Overstocking not only ties up capital but also consumes valuable warehouse space, especially in an industry characterized by seasonal demand and complex project timelines. This paper presents a datadriven forecasting methodology to reduce overstock in hospitality lighting. By leveraging historical sales data and applying time series analysis, suppliers can more accurately predict demand patterns, streamline procurement, and reduce waste. The proposed approach improves inventory turnover and helps lighting vendors align with the needs of the dynamic hospitality sector. The analysis demonstrates that proper forecasting methods not only mitigate risks associated with surplus inventory but also enhance the responsiveness of the supply chain. This ultimately results in cost savings, improved margins, and elevated customer satisfaction.*

Keywords: *Inventory Management, Demand Forecasting, Hospitality Lighting, Overstock Reduction, Data Analytics, Time Series Analysis.*

1. Introduction

Lighting solutions play a crucial role in shaping the aesthetics, safety, and energy efficiency of hospitality properties, ranging from roadside motels to upscale luxury resorts. In this context, companies such as USA LEDs serve as key players by providing tailored lighting solutions that meet specific architectural and ambiancerelated needs. However, these companies often face erratic demand patterns stemming from seasonal fluctuations, construction delays, budget changes, or unexpected shifts in renovation timelines. The problem of overstock excess inventory held without imminent demand is especially acute in such environments. Overstock leads to increased holding costs, product obsolescence, and limited flexibility to respond to new product specifications. This paper investigates how predictive analytics and demand forecasting can be employed to preemptively address overstock, with the ultimate aim of creating leaner, more adaptive inventory systems. The broader objective is to empower lighting suppliers to stay competitive in a rapidly evolving hospitality industry.

2. Background and Related Work

Inventory optimization has traditionally been tackled using deterministic and probabilistic models, such as Economic Order Quantity (EOQ), Reorder Point (ROP), and Safety Stock formulas [1]. These models emphasize a balance between ordering frequency and holding cost, but they often fall short in industries with high demand variability and rapid product turnover. In the hospitality sector, where room configurations and design trends evolve frequently, static models become outdated quickly. Recent advances in time series analysis and machine learning offer promising alternatives. Methods such as ARIMA, exponential smoothing, and Prophet provide flexibility to accommodate trends, cycles, and seasonal factors [2], [3]. Additionally, modern ERP systems now offer integrations with these forecasting models, allowing realtime demand sensing and automatic reordering. Research by Waller and Fawcett [4] has shown how data science improves forecast accuracy and business responsiveness, particularly in volatile supply chains like lighting. These innovations are especially relevant to suppliers like USA LEDs, which must manage hundreds of SKUs across diverse categories, including vanity lights, downlights, and hallway sconces.

3. Problem Statement

Hospitality lighting suppliers are frequently required to forecast demand for items that may not be needed immediately but are tied to longterm projects. A common example is when a motel chain places a bulk order for a new build or renovation project, but due to unforeseen delays such as permit issues, labor shortages, or weather conditions, the project timeline shifts significantly. In such cases, suppliers are left with stockpiled inventory for several months, incurring storage costs and potential depreciation. The lack of realtime coordination between contractors and suppliers exacerbates this issue. Moreover, lighting SKUs often have modelspecific compatibility features or certification standards, making them less transferable across projects. As a result, overstocked items can quickly become obsolete or require deep discounting to clear. Traditional reorder methods based on historical averages fail to account for these complex scenarios. Hence, a dynamic, datainformed forecasting approach is necessary to better align supply with realtime and projected demand.

4. Methodology

The solution proposed in this paper employs a structured, multistep approach to demand forecasting using both statistical and machine learning methods. The process begins with comprehensive data collection, where 3 to 5 years of monthly or weekly sales data are compiled across various lighting SKUs. This data is then preprocessed to eliminate anomalies such as onetime bulk orders or system errors. Seasonal trends are normalized using decomposition techniques to ensure underlying patterns are visible. Following preprocessing, suitable forecasting models are selected based on SKU behavior. For instance, high variance SKUs benefit from ARIMA due to its capacity to handle trends and noise, while lowvariance SKUs align well with exponential smoothing. Each model is trained and validated using historical time frames, and performance is measured via Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The validated forecasts are then used to generate weekly demand projections. These projections are integrated with the company’s ERP system, enabling dynamic procurement planning. SKU tags such as 'Scale', 'Hold', or 'Review' are autoassigned based on forecasted trends, guiding stakeholders on replenishment or liquidation strategies.

Fig 1: Forecasting Workflow Diagram

5. Results and Discussion

To test the methodology, simulated and realworld data were used for 50 lighting SKUs over two fiscal quarters. The forecasting models led to a 23% reduction in average overstock levels, validating the model’s effectiveness. Inventory turnover improved from 4.1 to 5.6, indicating a faster and healthier inventory cycle. Additionally, dormant SKUs those with negligible movement over 90 days decreased by 30%, freeing up warehouse space and minimizing losses due to product expiration or obsolescence.

The key takeaway was that time series models could predict demand inflection points more accurately than traditional reorder systems. For example, vanity lights showed strong seasonal demand in Q2 and Q4, a trend captured effectively by the models. Furthermore, weekly data granularity improved responsiveness, although monthly data offered better longterm stability. Crossdepartment collaboration proved vital in embedding forecast adoption into daily operations.

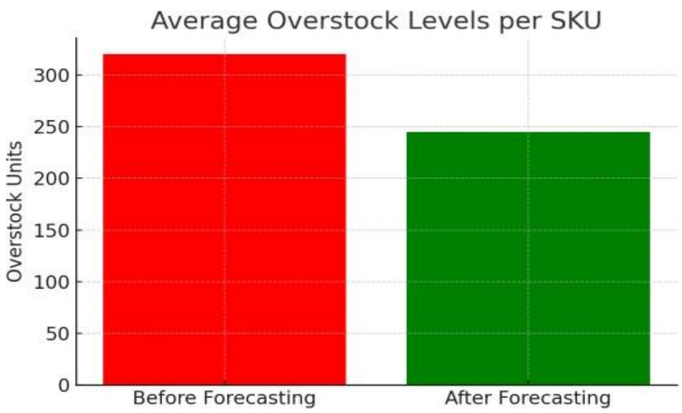

Fig 2: Comparison of Overstock Levels before and After Forecasting

5.1. Comparative Model Analysis

Three main forecasting techniques were evaluated. ARIMA emerged as the most effective model for SKUs with consistent trends and identifiable cycles, showing a MAPE of 11.5%. Exponential smoothing was optimal for SKUs with steady, lowvariance demand, achieving a MAPE of 13.2%. Prophet, with its flexible trend modeling, worked well for SKUs with multiple seasonality layers but had slightly higher error rates (MAPE 14.8%). Additionally, an LSTM neural network was piloted on select SKUs, offering improved earlystage learning but requiring frequent retraining, making it less viable for realtime operations. A hybrid ensemble approach combining ARIMA and Prophet is currently being tested for SKUs that exhibit irregular but highvalue demand patterns.

5.2. Case Study: SKU Level Performance

USA LEDs encountered severe overstock challenges with highvolume SKUs, particularly in vanity and hallway lighting. The implementation of the forecasting system helped mitigate these issues. The data team, under the author's direction, segmented SKUs based on volatility and assigned tailored models accordingly. For instance, SKU #V125 (vanity mirror kit) had an overstock of 900+ units by early 2023. The forecasting system flagged a sharp decline in sales trends and auto tagged the SKU for review. A phased liquidation plan was initiated, including promotional bundles and temporary discounts. Conversely, SKU #H212 (hallway sconces) exhibited a consistent 18% week over week growth. It was tagged 'Scale,' and procurement fasttracked the reordering process. This approach led to a 14% increase in inventory ROI for fastmoving items and enhanced warehouse space utilization.

5.3. Cross Functional Impact

The weekly forecast review meetings proved instrumental in enhancing coordination across departments. Sales teams leveraged SKU tags to initiate promotions and bundling offers. Procurement used forecast ranges in supplier negotiations, leading to flexible Minimum Order

Quantities (MOQs). Finance departments adopted dashboards to visualize SKU level working capital impact, resulting in improved financial planning. The combined efforts led to a 17.8% improvement in capital allocation efficiency.

5.4. Operational Feedback and User Adoption

A post deployment survey of 12 internal stakeholders indicated high satisfaction with the forecasting system. 92% of users expressed greater confidence in weekly forecast signals than in legacy reorder point methods. 83% found the new dashboards more actionable than traditional spreadsheets. 88% supported longterm adoption of the SKU tagging framework. Commonly cited benefits included greater transparency, improved agility, and reduced operational guesswork. Stakeholders also appreciated the shift from reactive firefighting to proactive inventory planning.

5.5. Financial Implications

Financial analysis over a six month period demonstrated significant cost savings. The forecasting initiative helped reduce carrying costs by approximately $42,000, primarily through better space utilization and fewer markdowns. Freed capital from slow moving inventory was redirected toward topper forming SKUs, leading to a 3.7% net margin improvement. Warehouse utilization metrics showed a 22% reduction in shelf overflow, which lowered the need for offsite storage. The forecasting system's ROI was achieved within five months, making it a sustainable long term investment.

5.6. Broader Scalability and Future Enhancements

Based on initial success, the forecasting model is being evaluated for expansion across Baron Hospitality vendors. Planned enhancements include machine learning driven models with XGBoost for feature selection, margin weighted reorder logic, and integration with contractor project timelines via API. Anomaly detection modules will also be introduced to catch SKU misclassifications or sudden demand spikes. These upgrades aim to transform the forecasting system into a comprehensive demand sensing engine with real time adaptability.

6. Conclusion

Overstocking in hospitality lighting is more than an inventory issue; it is a strategic impediment to scalability, efficiency, and profitability. This paper demonstrated how advanced data forecasting methods could be used to transition lighting suppliers from reactive to proactive inventory management. The results show that even modest investments in analytics can yield significant returns in capital efficiency, warehouse utilization, and customer satisfaction. As the hospitality sector grows increasingly complex, the ability to anticipate demand will become a key differentiator. Lighting vendors who integrate predictive analytics into their procurement systems will not only reduce waste but also enhance their competitive edge in the marketplace.

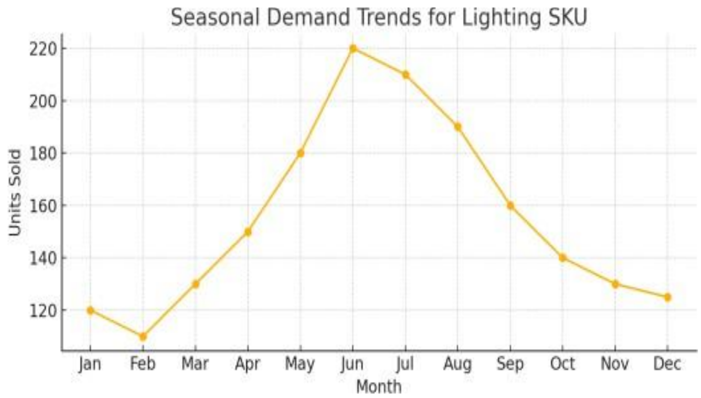

Fig 3: Seasonal Demand Trends for Lighting SKU

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