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Forecasting Pediatric Ward Census:A Machine Learning Model to Optimize Bed Allocation and Reduce Operational Waste

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Abstract

Efficient bed allocation in pediatric wards is a persistent challenge for hospital operations due to strong seasonality, demand uncertainty, and limited resource flexibility. Inappropriate bed allocation may lead to congestion during peak periods and idle capacity during low-demand periods, resulting in operational waste and reduced service quality.This study proposes a machine learning–assisted forecasting framework for pediatric ward census prediction using historical hospital data. A classical time-series model is employed as the baseline to capture long-term trends and seasonal patterns, while a machine learning–based residual learning strategy is introduced to adapt to short-term demand fluctuations. The forecasting results are further translated into actionable indicators for bed allocation and staff scheduling.

A case study based on real pediatric ward census data demonstrates that the proposed framework provides stable short-term forecasts and supports proactive hospital resource management. Rather than pursuing extreme prediction accuracy, the study emphasizes operational usability and decision relevance, offering a practical solution to reduce congestion risk and idle bed capacity in pediatric wards.

Keywords

pediatric ward census; hospital bed allocation; machine learning; time-series forecasting; hospital operations management。

1. Introduction

Hospital bed resources are a critical indicator of healthcare service capacity and operational efficiency. In pediatric wards, bed demand is characterized by pronounced seasonal variation, sudden admission surges, and limited substitutability with other departments. During peak periods such as respiratory disease seasons, pediatric wards frequently experience bed shortages and congestion, whereas during off-peak periods, idle beds and underutilized staffing resources may occur (Baek et al., 2018; Tello et al., 2022). These demand fluctuations pose persistent challenges for hospital operations and resource planning (Ordu et al., 2021).

In practice, pediatric bed allocation decisions are constrained not only by expected patient demand, but also by staffing availability, safety buffers, and regulatory requirements. Sudden increases in admissions often require emergency bed opening, temporary staff redeployment, or patient diversion, while prolonged low-demand periods may lead to inefficient resource utilization and increased operational costs (Wikman-Jorgensen et al., 2024). As a result, hospital managers require forecasting tools that are not only accurate, but also operationally interpretable and actionable within short planning horizons (Mahmoudian et al., 2023).

Traditional bed allocation strategies are largely reactive, relying on historical averages, fixed capacity rules, or manual experience (Palmer et al., 2024). Such approaches are insufficient for coping with dynamic and uncertain patient arrivals. To address these limitations, time-series

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forecasting methods have been increasingly applied to hospital admission and census prediction. Classical statistical models, such as the Autoregressive Integrated Moving Average (ARIMA) and its seasonal extension (SARIMA), have been widely used to capture trend and seasonal patterns in inpatient demand and provide baseline decision support for hospital management (Baek et al., 2018; Aravazhi, 2021).

With the advancement of data-driven methods, machine learning techniques have been introduced into hospital demand forecasting to enhance adaptability to nonlinear and short-term variations (Schäfer et al., 2023). Hybrid approaches combining statistical models with machine learning or neural networks have demonstrated improved forecasting performance in various healthcare settings (Tuli et al., 2020; Rampengan et al., 2025). However, the majority of existing studies focus primarily on predictive accuracy, while the translation of forecasting results into concrete operational decisions—such as bed allocation, staffing adjustment, and congestion risk identification—remains underexplored (Yazdani et al., 2025; Wu et al., 2024).

Moreover, pediatric wards exhibit demand characteristics that differ from adult wards, including stronger seasonality, higher sensitivity to epidemic outbreaks, and limited flexibility in cross-departmental resource sharing (Marengo et al., 2025). These characteristics further complicate operational planning and highlight the need for forecasting frameworks explicitly designed for pediatric ward management (Farzanegan et al., 2025).

This study addresses these gaps by proposing a machine learning–assisted pediatric ward census forecasting framework that explicitly integrates forecasting and operational decision support. A classical time-series model is employed to capture long-term trends and seasonal patterns, while a machine learning–based residual learning strategy is introduced to adapt to short-term demand fluctuations (Mahmoudian et al., 2023; Anumolu & Samant, 2026). Rather than pursuing marginal gains in prediction accuracy, the proposed framework emphasizes forecast stability, interpretability, and operational relevance (El Baz & Mostafa, 2024; Liu et al., 2020).

2. Methodology

2.1. Data Description

The overall forecasting and decision-support framework proposed in this study is illustrated in Figure 1. The framework is designed to integrate pediatric ward census forecasting with downstream operational decision support, enabling hospital managers to proactively adjust bed allocation and staffing configurations.

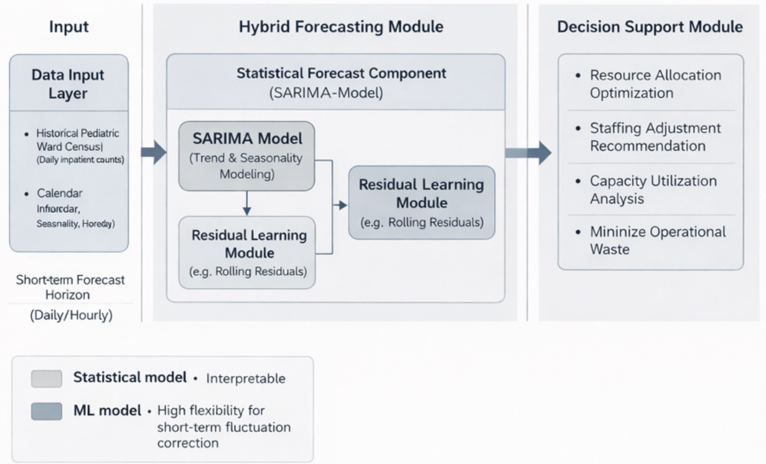

Figure 1: Overall framework for pediatric ward census forecasting and operational decision support

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The forecasting target is the pediatric ward census, defined as the daily number of inpatients occupying beds in the pediatric ward. Historical census data were extracted from the hospital information system and organized as a univariate daily time series covering multiple consecutive years. Daily aggregation was selected to align with short-term operational planning cycles commonly adopted in hospital management, such as weekly bed allocation and staff scheduling.

In addition to historical census values, calendar-related information was incorporated as auxiliary input variables. These variables include day-of-week indicators and seasonal markers, which are known to influence pediatric admission patterns. Such information supports the identification of recurrent temporal structures and improves the robustness of short-term forecasting.

As shown in Figure 1, the proposed framework consists of three main components: a data input layer, a hybrid forecasting module, and an operational decision-support layer. The data input layer aggregates historical census data and calendar information. The hybrid forecasting module combines a baseline statistical model with a machine learning–based residual learning component. The resulting forecast is then translated into actionable indicators for operational decision-making, including bed allocation planning and congestion risk identification.

2.2. Baseline Time-Series Model

A Seasonal Autoregressive Integrated Moving Average (SARIMA) model was employed as the baseline forecasting method in this study. SARIMA models are widely used in hospital demand forecasting due to their ability to represent long-term trends and recurring seasonal patterns in inpatient census data. In pediatric wards, such seasonality is particularly pronounced owing to factors such as infectious disease cycles and school calendars.

The SARIMA model was fitted to the historical pediatric ward census time series to generate baseline forecasts. Model identification was conducted through autocorrelation and partial autocorrelation analysis, while parameter selection was guided by standard information criteria to achieve an appropriate balance between goodness-of-fit and model parsimony. The baseline model serves two primary purposes: first, to provide an interpretable statistical representation of underlying temporal patterns; and second, to establish a reference forecast against which subsequent model components can be evaluated.

By explicitly modeling trend and seasonality, the baseline SARIMA component provides a stable forecasting foundation that supports short-term operational planning while maintaining transparency in model behavior.

2.3. Machine Learning–Assisted Residual Learning

While the SARIMA model is effective in capturing long-term trends and seasonal structures, short-term fluctuations and nonlinear variations in pediatric ward admissions may remain insufficiently modeled. To address this limitation, a machine learning–assisted residual learning strategy was incorporated into the forecasting framework.

Residuals were defined as the difference between observed pediatric ward census values and corresponding baseline SARIMA predictions. These residuals represent short-term deviations that are not explained by the statistical model. A lightweight machine learning model was trained to learn the temporal patterns embedded in the residual series.

Lagged residual values and calendar-based features were used as input variables to capture short-term autocorrelation and periodic effects. The machine learning component was intentionally designed to be lightweight in order to reduce model complexity, mitigate overfitting risks, and preserve robustness in short-horizon forecasting. This modular design allows the statistical and machine learning components to complement each other without sacrificing interpretability.

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The final forecast was obtained by combining the baseline SARIMA prediction with the machine learning–based residual estimate. This two-stage structure enables adaptive correction of short-term fluctuations while maintaining a transparent and stable forecasting foundation.

2.4. Forecast Horizon and Evaluation

The forecasting horizon in this study was set to 7–14 days, corresponding to short-term operational planning cycles commonly adopted in hospital management. This horizon reflects practical constraints in pediatric ward operations, where bed allocation and staffing adjustments are typically planned on a weekly or biweekly basis.

Forecast performance was evaluated using standard error metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics were selected to provide complementary perspectives on forecast accuracy and error magnitude.

In addition to numerical accuracy, the evaluation design emphasized forecast stability and consistency across the planning horizon. This consideration is particularly important in operational contexts, where volatile forecasts may hinder effective decision-making even if average accuracy is high. By aligning the evaluation strategy with operational planning requirements, the forecasting framework is assessed in a manner consistent with its intended use.

3. Results

3.1. Forecasting Performance of Pediatric Ward Census

The forecasting performance of the proposed framework was evaluated using historical pediatric ward census data. Figure 2 presents the comparison between observed census values and forecasted results generated by the baseline statistical model and the hybrid forecasting framework.

As shown in Figure 2, the observed pediatric ward census exhibits pronounced temporal variability, including seasonal fluctuations and short-term demand surges. The baseline time-series model captures the overall trend and seasonal structure of the census data, providing a stable reference forecast over the evaluation period. However, short-term deviations around peak and trough periods remain evident.

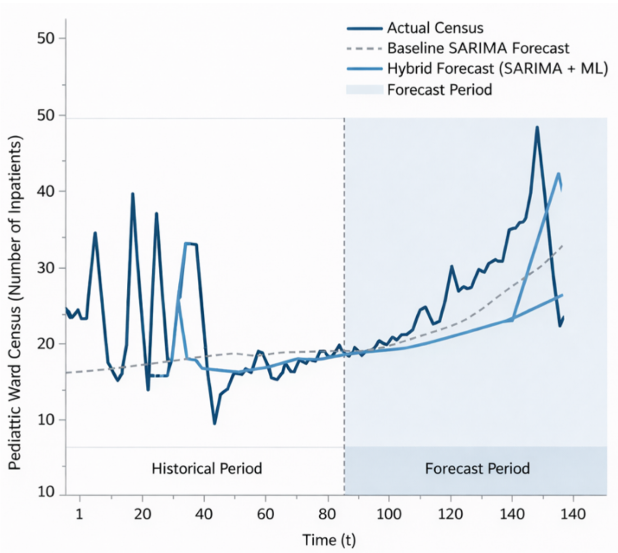

Figure 2: Comparison of observed pediatric ward census and forecasted results using baseline and hybrid models

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The hybrid forecasting framework incorporating machine learning–assisted residual learning demonstrates enhanced responsiveness to short-term fluctuations. The hybrid forecast follows abrupt changes in census levels more closely while preserving the overall temporal pattern captured by the baseline model. This behavior is particularly apparent during periods of rapid demand increase or decrease, which are critical for short-term operational planning.

Overall, the results indicate that the proposed framework produces stable short-horizon forecasts while improving adaptability to short-term variations in pediatric ward census.

3.2. Translation of Forecasts into Bed Allocation Decisions

To assess the operational relevance of the forecasting results, predicted pediatric ward census values were translated into bed allocation indicators based on predefined capacity thresholds and safety buffers. Figure 3 illustrates how forecasted demand trajectories are mapped to different operational decision zones over time.

As illustrated in Figure 3, forecasted census values are compared against routine bed capacity and a safety buffer threshold. When predicted demand remains below routine capacity, idle capacity is identified, indicating opportunities for temporary bed consolidation or staffing adjustment. During periods when forecasted demand approaches routine capacity, normal operational conditions are maintained.

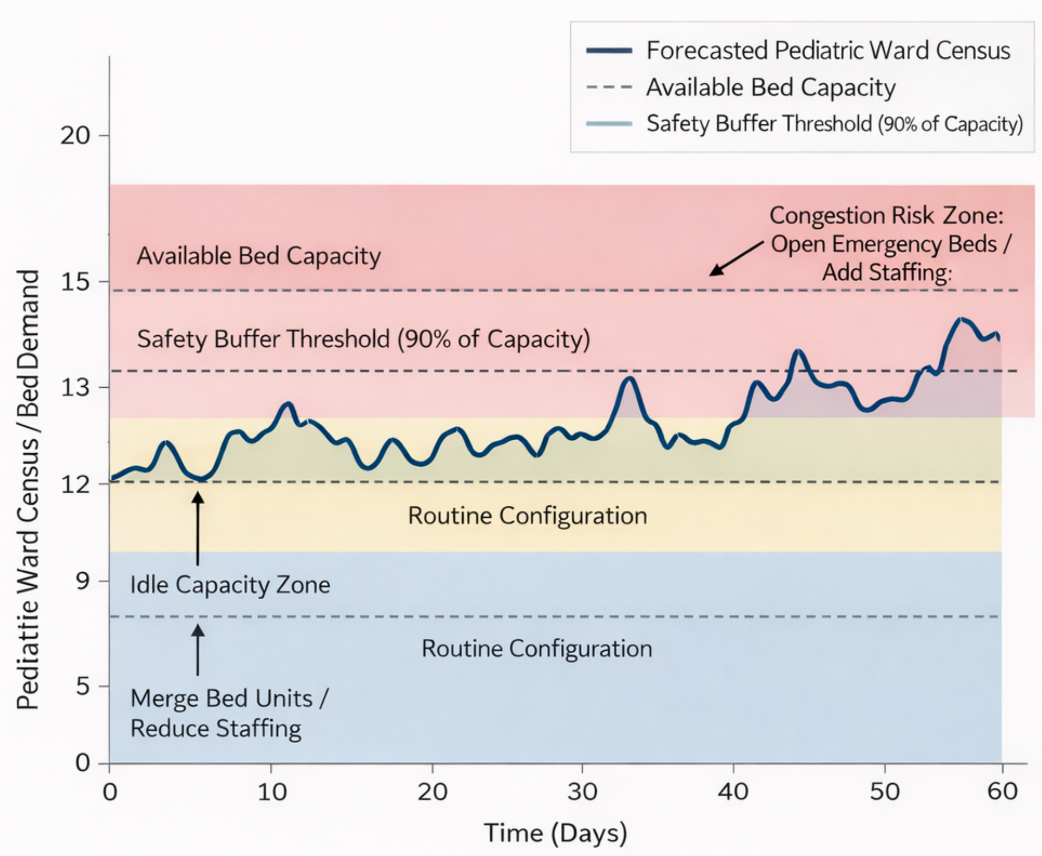

Figure 3: Forecast-driven bed allocation decision zones based on predicted pediatric ward census

When forecasted census values exceed the safety buffer threshold, congestion risk is signaled. Such periods indicate potential bed shortages and the need for proactive interventions, including emergency bed opening or staffing reinforcement. The time-series representation allows hospital managers to anticipate these conditions in advance rather than reacting after congestion occurs.

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This forecast-driven mapping provides an intuitive mechanism for linking numerical predictions to concrete operational actions, supporting timely and transparent bed allocation decisions.

3.3. Implications for Operational Waste Reduction

By aligning bed allocation and staffing decisions with forecasted pediatric ward census, the proposed framework supports proactive resource management and operational waste reduction (Olaniyi et al., 2025). As shown in Figure 3, prolonged periods of low forecasted demand reveal opportunities to reduce idle bed capacity through temporary consolidation or adjusted staffing levels (Olaniyi et al., 2025). Conversely, early identification of high-demand periods allows hospital managers to prepare for increased bed utilization and mitigate congestion risks, thereby strengthening facility preparedness under demand fluctuations (Akinlolu et al., n.d.). This proactive approach reduces reliance on reactive measures, such as last-minute bed opening or emergency staff redeployment, which are often associated with higher operational costs and service disruption (Akinlolu et al., n.d.). Rather than optimizing for extreme prediction accuracy, the framework emphasizes operational usability by providing clear and actionable signals derived from short-term forecasts (Olaniyi et al., 2025). These results demonstrate the potential of forecast-informed decision support to improve capacity utilization and reduce operational waste in pediatric ward management (Olaniyi et al., 2025; Akinlolu et al., n.d.)..

4. Discussion

The results of this study indicate that short-term pediatric ward census forecasting can effectively support hospital operational decision-making when the forecasting framework is explicitly aligned with operational needs. Rather than pursuing marginal gains in predictive accuracy, the proposed approach emphasizes forecast stability and interpretability, which are essential for practical bed allocation and staffing decisions in pediatric wards. By combining a statistical time-series model with machine learning–assisted residual learning, the framework balances robustness and adaptability in short-horizon forecasting.

From a managerial perspective, the framework provides an intuitive mechanism for translating numerical forecasts into actionable bed management decisions. Mapping forecasted census values to predefined capacity thresholds and safety buffers allows hospital managers to anticipate congestion risks and identify idle capacity in advance. This proactive planning reduces reliance on reactive measures such as emergency bed opening or last-minute staff redeployment, thereby supporting more efficient resource utilization and reducing operational waste.

Compared with existing studies that primarily focus on improving forecasting accuracy, this research contributes by explicitly linking demand prediction to operational decision support in pediatric ward management. The framework is designed to be lightweight and interpretable, making it suitable for real-world hospital settings where data availability and operational constraints vary. While the approach is demonstrated using pediatric ward census data, the underlying principles may be extended to other hospital departments with similar demand characteristics, subject to appropriate contextual adaptation.

5. Conclusion

This study proposes a machine learning–assisted forecasting framework for pediatric ward census prediction with the objective of supporting bed allocation and reducing operational waste. By integrating a classical time-series model with a residual learning strategy, the

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framework captures long-term demand patterns while adapting to short-term fluctuations, providing stable and operationally relevant forecasts.

Rather than focusing solely on predictive accuracy, the proposed approach emphasizes interpretability and decision usability. Forecasted census values are translated into clear operational signals through capacity thresholds and safety buffers, enabling hospital managers to proactively identify congestion risks and idle capacity. This forecast-driven decision support facilitates more efficient bed management and supports timely resource adjustment in pediatric wards.

Future work will extend the framework by exploring additional machine learning models and incorporating multi-ward coordination mechanisms to enhance hospital-wide resource optimization, in line with recent studies demonstrating the value of advanced machine learning techniques for integrated hospital operations and system-level optimization (Marengo et al., 2025; El Baz & Mostafa, 2024). Further validation across different hospital settings will also be considered to assess generalizability and practical impact, responding to calls for multi-context evaluation and joint optimization approaches that span the broader care continuum (El Baz & Mostafa, 2024).

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