# Proactive Forecasting with a Digital Twin in Emergency Departments: Preserving Key Performance Indicators Values

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**Abstract.** Efficient management of hospital Emergency Departments (EDs) is essential to prevent service saturation or bottlenecks caused by unexpected patient inflows and resource limitations. This work proposes a Digital Twin (DT) framework that simulates ED operations to anticipate performance degradation and support proactive decision-making. The DT operates faster than the real system, enabling exploration of future operational scenarios and evaluation of corrective staffing strategies. A heuristic optimization method is used to identify personnel configurations that preserve Key Performance Indicators (KPIs) under disruptive demand conditions while respecting resource constraints. Results show that the proposed DT supports early detection of KPI degradation risks and enables timely staffing adaptation to maintain ED operational performance.

**Keywords:** Decision Support · Digital Twin · Emergency Department · Optimization · Simulation · Prevention · Key Performance Indicators

## 1 Introduction

EDs are critical hospital units characterized by high variability in patient inflow, complex resource interactions, and strong dependence on staffing availability. These factors make maintaining service quality and operational efficiency particularly challenging, especially under unexpected demand surges.

Traditional ED management relies on reactive decision-making once performance degradation becomes visible. In contrast, DT technology enables proactive control by replicating system behavior and forecasting future operational

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conditions through accelerated simulation. Fig. 1 illustrates the transition from traditional reactive management to a DT-based predictive control loop for ED operation.

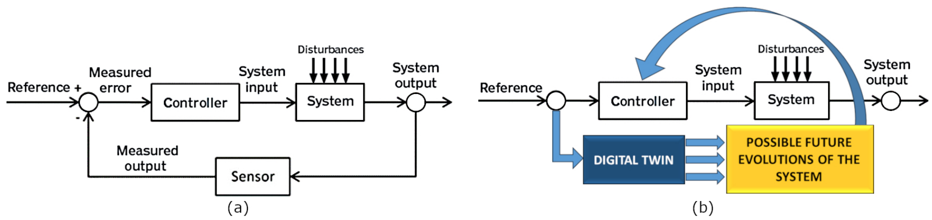


**Fig. 1.** (a) Feedback control loop. (b) Digital twin-based control.

DT technology is increasingly used in healthcare as a predictive decision-support framework for complex systems. Existing applications include medical device monitoring and organ-level modeling [7,11], although they mainly focus on patient-specific scenarios rather than hospital operations. DT-based solutions have also been applied to hospital workflow optimization and emergency resource planning [2,3,10]. However, these approaches typically rely on descriptive simulation and do not support proactive control under dynamic demand conditions.

Although agent-based simulation has proven effective for modeling ED dynamics [5,6,9], the integration of DT-based predictive modeling with staffing adaptation driven by optimization remains limited.

This work proposes a DT-based framework that anticipates KPI degradation and evaluates corrective staffing configurations before disruptions affect the real system. Suitable configurations are identified using the Monte Carlo Clustering Search Algorithm (MCSA), a stochastic sampling-based heuristic optimization method integrated within the DT environment to evaluate alternative staffing strategies and mitigate performance degradation proactively.

## 2 Management of the ED through a DT

The objective of this research is to improve ED management using a DT that simulates its operations to anticipate its behavior.

### 2.1 ED simulator

The DT relies on a stochastic agent-based ED simulator developed by the High Performance Computing for Efficient Applications and Simulation (HPC4EAS) research group at the Universitat Autònoma de Barcelona (UAB) and calibrated using historical data from Hospital Parc Taulí in Sabadell [4,5]. Its stochastic formulation enables realistic representation of patient flow variability and supports the evaluation of alternative staffing configurations under varying arrival patterns and resource constraints.

The validity of the proposed DT is ensured through calibration and validation of the underlying agent-based modeling and simulation (ABMS) ED simulator

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framework using historical operational data. Model outputs were compared with observed KPI values to verify consistency between simulated and real system behavior. In addition, periodic data updates allow recalibration when deviations are detected, maintaining alignment between the physical ED and its digital counterpart over time.

### 2.2 Model Inputs and Outputs

To support decision-making, the ED model considers key input parameters including patient inflow classified according to the Spanish Triage System [8], physical resources (e.g., beds, laboratories, and test units), and healthcare staffing composition. Patients are treated in two care areas based on triage priority: Area A (levels 1–3) and Area B (levels 4–5). Staffing configurations account for both the number of professionals and their experience level (junior and senior), which influences service times and system performance.

System performance is evaluated through several KPIs [12], including Length of Stay (LoS), Length of Waiting Time (LoW), Patient Attention Time (PaT), and staffing occupation indicators. Among these, LoS is used as the primary indicator of operational performance due to its relevance for ED efficiency and service quality. The simulator provides LoS estimates by triage level $i \in \{1, 2, 3, 4, 5\}$; in this work, the overall average LoS is used as a global efficiency indicator to compare operational scenarios.

### 2.3 Digital Twin Operation

The ED receives patients classified by triage level and operates under target KPI conditions. As shown in Fig. 2, the DT is configured with the same healthcare staff (HS) and physical resource (PR) parameters as the real system and receives identical patient inflow data updated dynamically over time.

The proposed system maintains continuous correspondence between the physical ED and its digital replica through calibrated simulation models and operational inputs. Unlike a standalone simulation model, the DT preserves synchronization with the physical ED through periodic data updates and recalibration mechanisms. This enables the DT not only to reproduce system behavior but also to anticipate performance deviations and evaluate corrective actions before their implementation in the real environment, acting as a predictive decision-support layer within the ED management loop.

By executing simulations faster than real time to explore alternative future scenarios, the DT enables early identification of staffing configurations that preserve target KPI values. Due to the multidimensional interaction among decision parameters, the search process is performed using a heuristic optimization method based on Monte Carlo sampling, referred to as MCSA [1], which efficiently explores the configuration space through stochastic sampling and simulation-based evaluation without exhaustive enumeration.

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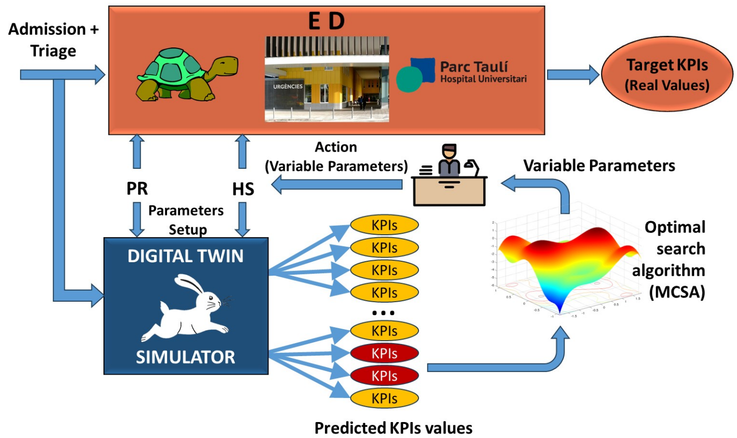


**Fig. 2.** Operation of the ED Digital Twin

## 3 Monte Carlo Clustering Search Algorithm

To identify suitable medical staffing configurations in the ED, the MCSA heuristic optimization method is employed. MCSA alternates between exploration and intensification phases, exploring the multidimensional configuration space through stochastic sampling combined with simulation-based evaluation of candidate solutions using the ABMS simulator.

The method can be interpreted as a stochastic simulation-based optimization approach that combines Monte Carlo sampling with clustering-driven intensification. Candidate staffing configurations are evaluated using the ED simulator model, and the search is iteratively biased towards high-performing regions of the solution space identified through clustering, enabling efficient identification of suitable configurations without exhaustive enumeration.

The algorithm iteratively evaluates staffing configurations according to their impact on KPIs (e.g., mean LoS) and refines the search until convergence is achieved. From a computational perspective, the method scales with the dimensionality of the configuration space, and since candidate evaluations are independent, it is naturally parallelizable through concurrent simulation runs.

## 4 DT Integration for Predictive Optimization in ED

### 4.1 Predictive Simulation and Disruption Management

As a first step, the proposed framework identifies staffing adjustments required to prevent abnormal operating conditions and avoid ED saturation. As illustrated in Fig. 3, the system is periodically monitored at one-hour intervals, and predictive simulations are executed on the DT to detect potential deviations from target KPI values. When performance degradation is anticipated, the MCSA heuristic algorithm is applied to identify suitable staffing configurations. The selected

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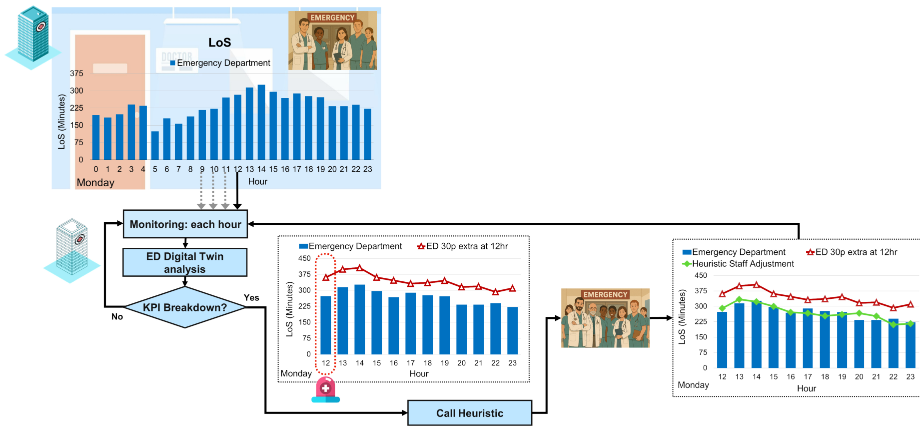


**Fig. 3.** Predictive Simulation and Disruption Management Process

configuration is then validated through simulation to ensure that KPI levels remain within acceptable limits.

At each monitoring interval, predicted KPI values obtained from the DT are compared with observed values from the real ED. When deviations exceed a predefined threshold, a recalibration process is triggered by updating model input parameters using recent operational data, ensuring continuous alignment between the digital and physical systems.

## 4.2 Intervention window

Once the appropriate staffing adjustments have been identified, the intervention window is defined as the time available to implement corrective actions before performance degradation affects the real ED. This window is estimated by simulating disturbance scenarios with increased patient inflow and monitoring the evolution of the LoS over time (Fig. 4(a)).

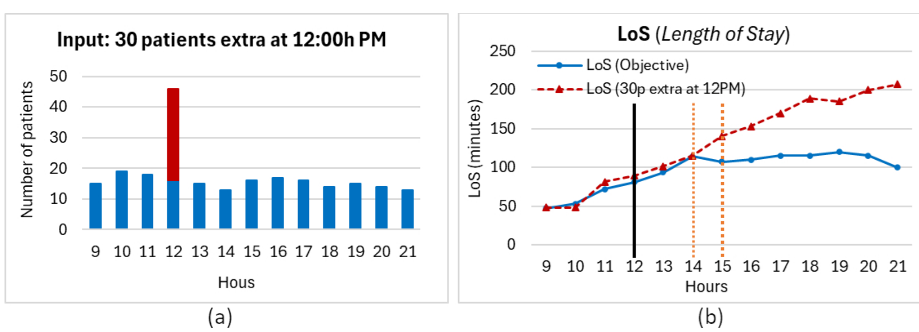


**Fig. 4.** (a) Scenario: Surge of 30 additional patients at 12:00 PM. (b) Comparison of LoS values between the target and the scenario with additional patients at 12:00 PM.

As shown in Fig. 4(b), a noticeable deviation in LoS appears between the second and third hour after the disturbance, defining the available intervention

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window. Early identification of this interval enables timely corrective actions to stabilize system performance and prevent service disruptions.

## 5 Advanced Management Case ED/DT

To maintain ED operation within the target range of the selected KPI (LoS) under unusual patient inflow conditions, the proposed strategy adjusts staffing configurations through targeted temporary reinforcement of healthcare personnel. The operational parameters considered in this case study are summarized in Table 1.

**Table 1.** Initial and optimized staffing configuration for the ED (SD: Senior doctor, JD: Junior doctor, SN: Senior nurse, JN: Junior nurse)

| | Area A | | Area B | |
|---|---|---|---|---|
| Role | Initial | Optimized | Initial | Optimized |
| JN | 2 | 2 | 5 | 6 |
| SN | 3 | 3 | 7 | 4 |
| JD | 2 | 2 | 5 | 3 |
| SD | 3 | 7 | 2 | 7 |

In the initial phase, the DT is configured to replicate the operational conditions of the ED. Disturbance scenarios are generated by injecting additional patients at specific hours; as an illustrative example, a surge of 30 extra patients at 12:00 p.m. on a Monday is considered. Simulation results show that this disturbance produces a significant increase in average LoS beyond the target threshold, indicating a potential overload situation. To mitigate this effect, the MCSA heuristic method identifies a feasible staffing reconfiguration under realistic resource constraints (Table 1). The updated configuration is then evaluated through simulation using the DT. As shown in Fig. 5, the adjusted staffing plan restores the average LoS to the target range.

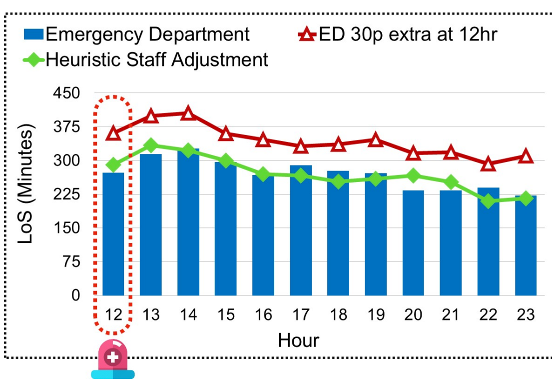


**Fig. 5.** Comparison of Scenario LoS, Target LoS, and LoS after staffing adjustment

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These results highlight the capability of the DT framework to anticipate performance degradation and support proactive staffing adjustments before disruptions affect the real ED.

The results demonstrate that the proposed DT supports proactive staffing optimization and provides insight into system behavior under varying demand conditions, enabling corrective actions before performance degradation affects the real ED.

## 6 Conclusion

This work demonstrates the potential of DT technology to support proactive management of hospital EDs by anticipating performance degradation and evaluating corrective staffing strategies through accelerated simulation. The integration of the MCSA heuristic method enables efficient identification of staffing configurations that preserve service quality under disruptive patient inflow conditions.

A key contribution of this study is the definition of the intervention window, identified as the critical 2–3-hour period following a disturbance, during which corrective actions can be applied before system performance deteriorates.

Results also highlight the need to balance KPI improvement with operational feasibility, since configurations that minimize LoS may not always correspond to the most efficient use of resources. The DT environment enables validation of alternative staffing strategies before implementation, reducing operational risk and supporting informed decision-making.

Overall, the proposed DT-based framework provides an effective predictive decision-support tool for improving resilience and operational efficiency in Emergency Departments.

## 7 Future Work and Ethical Considerations

Future work will focus on extending the DT with additional system parameters and KPIs to better capture the interactions affecting ED performance, as well as validating the proposed framework in different hospital environments to assess its generalizability. Further research will also address the integration of real-time operational data streams to improve model calibration and support continuous alignment between the physical ED and its digital counterpart.

From an ethical perspective, the use of hospital operational data requires strict compliance with data protection regulations such as General Data Protection Regulation (GDPR). Although the proposed DT does not rely on individual patient identification, ensuring transparency in model assumptions and preventing bias in decision-support recommendations remain essential for responsible deployment in clinical environments.

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