Optimising Healthcare Resource Allocation Through Patient Treatment List Consolidation: A Mathematical Simulation and Machine Learning Approach

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Abstract

Multiple Patient Treatment Lists (PTLs) across multiple healthcare providers within Integrated Care Systems create significant inefficiencies in the utilisation of the resources and unjust patient access to care. This research addresses a critical challenge faced by the Cambridgeshire and Peterborough Integrated Care Board (ICB), where individual NHS providers maintain separate Patient Transport Lists (PTLs), leading to scenarios where providers experience long waiting lists while neighbouring providers possess unused capacity in similar specialities.

This study develops a comprehensive mathematical framework that combines discrete event simulation, queueing theory, and machine learning optimisation to model and evaluate the consolidation of multiple provider-specific PTLs into a single, coordinated PTL. The methodology employs a multi-phase approach utilising anonymised patient data from the Cambridgeshire and Peterborough ICB to establish baseline performance metrics, followed by M/M/c queueing systems and discrete event simulation to capture patient flow dynamics. Advanced machine learning techniques, including time series forecasting (ARIMA, Prophet) and reinforcement learning, will optimise patient allocation and resource scheduling across the consolidated system.

The aim is to achieve a gain of approximately 15-40% in resource utilisation and 25-40% reductions in patient waiting times through combining the PTL and suggesting to the patients the provider with the minimum waiting time. Expected outcomes include a validated mathematical framework for PTL consolidation, evidence-based recommendations for ICB strategic decision-making aligned with NHS 2025/26 Operational Plan goals, and broader methodological contributions to healthcare operations research. The project intends to provide crucial insights that will help the NHS adopt integrated care delivery models to preserve clinical quality and drastically bring down patient wait times, especially post-COVID-19.

Ethics Statement

This project did not require ethical review, as determined by my supervisor Joshua Ramini.

I have completed the ethics test on Blackboard. My score is 12/12.

Project Plan

Introduction and Motivation

The NHS is under increasing pressure to deliver healthcare in a post-COVID-19 world, facing growing patient demand and limited resources. Elective care backlogs have further intensified this challenge, making the efficient use of existing capacity more critical than ever. Patient Treatment Lists (PTLs) are currently maintained separately by different providers; however, this fragmented approach often results in inefficient resource utilisation. In the Cambridgeshire and Peterborough Integrated Care Board (ICB), independently managed PTLs lead to unequal waiting times, underutilised clinical capacity, and disparities in access to care. Given that surgical services account for 10–30% of hospital expenditures, optimising surgery scheduling and resource allocation could result in significant cost savings (Cardoen, Demeulemeester, & Beliën, 2010).

The NHS Long Term Plan and local ICB strategies call for more integrated models of care. A single PTL approach—where referrals are pooled and dynamically allocated across the system—offers the potential to enhance equity, reduce delays, and balance workloads more effectively. Lessons from other domains reinforce this approach. For example, airports manage unpredictable passenger flow using centralised queueing systems (Wu & Mengersen, 2013), while traffic engineering applies mathematical models to optimise capacity usage in complex, distributed networks (Helbing, 2001). This research leverages such parallels to propose a data-driven strategy for NHS patient flow optimisation.

Methodology

This research explores consolidating multiple provider-specific PTLs into a single PTL and redistributing the patients to the providers who have underutilised resources. The technical approach is a combination of established research methodologies with advanced machine learning techniques to address the complex optimisation, especially for a large-scale healthcare system.

Phase 1: Data Collection and Baseline Analysis

This phase focuses on obtaining the necessary data, understanding it, cleaning it, and analysing NHS administrative data. The data is expected to have data including monthly records of surgeries performed, procedure types (e.g., cataracts), patient demographics, and reported capacity of the provider, along with the average number of surgeons available. Performing EDA will help in identify trends, seasonal patterns, outliers, and baseline statistics such as average waiting times, cancellations, and throughput.

Phase 2: Mathematical Modelling using Queueing Theory
This phase will aim to provide a structured mathematical framework for modelling waiting systems. Discrete event simulation will be used as the foundational approach, with systematic reviews by Landa, Sonnessa, Tànfani, and Testi (2021) demonstrating 15–40% efficiency improvements when combined with optimisation techniques across 231 healthcare applications. The model will first use M/M/c queues where the arrival of the patients is modelled as a Poisson distribution, service times of the provider follow exponential distributions, and c will represent available surgical theatres per provider. Each provider will be modelled as a separate queue, then compared to a consolidated system using Little's Law ($L = \lambda W$) and related formulas. Studies by Santibañez, Chow, French, Puterman, and Tyldesley (2009) and Green, Soares, Giglio, and Green (2006) show 15–78% efficiency gains through queueing-based resource reallocation.

Phase 3: Discrete Event Simulation (DES) Implementation

This phase's primary focus will be on capturing real-world complexity beyond static models through flexible representation of resource availability and complex patient pathways. We will use Python's SimPy library to implement the DES, which will model individual patient flow from referral to treatment,

incorporating stochastic arrival rates, patient priorities, and scheduling constraints. The DES will also test various scenarios, such as shared weekend sessions, patient reprioritisation, and dynamic routing. It will also facilitate experimentation with merged versus fragmented PTLs. Günal and Pidd (2010) demonstrated the utility of DES in capturing such hospital dynamics.

Phase 4: Machine Learning Integration and Optimisation

This phase aims to develop predictive models using time series forecasting and reinforcement learning approaches. Using time series models, such as ARIMA and Prophet, will help us model future demand by provider and procedure type. Zhang, Zhang, Haghani, and Zeng (2018) demonstrated that hybrid models outperform classical forecasting approaches. We aim to optimise using a Mixed-Integer Linear Programming for constrained scheduling and patient allocation as demonstrated by Beliën and Demeulemeester (2007) to achieve optimal solutions in healthcare resource allocation. Reinforcement learning for dynamic policy optimisation under uncertainty will help in reducing average waiting time and enhancing utilisation. Recent studies by Moosavi, Fatollahi-Fard, and Dulebenets (2023) show integrated forecasting-optimisation frameworks achieving 10.81% performance improvements while reducing patient waiting times by 8.17% with Mean Absolute Percentage Error values below 3%.

Phase 5: Evaluation and Comparison

The evaluation will be done by validation of the models with historical data, sensitivity analysis, and scenario testing (separate vs. merged PTLs). Track key performance indicators like wait times, equity, utilisation, and cancellations. We will compare mathematical simulation results with machine learning optimisation outcomes, providing a comprehensive evaluation mapped to the NHS 2025/26 Operational Plan goals.

Expected Outcomes

This project aims to provide a validated simulation-optimisation framework that models merging various PTLs into a single PTL and quantifies the impact across the system. A 15-40% increase in resource utilisation, 25–60% reductions in average waiting times, and Greater fairness in patient access across providers are expected. It will provide evidence-based recommendations for ICBs, including implementation of roadmaps. By integrating DES and machine learning, the research offers innovative solutions for multi-provider resource sharing, supporting NHS transformation toward integrated care systems.

References

Beliën, J., & Demeulemeester, E. (2007). Building cyclic master surgery schedules with leveled resulting bed occupancy. *European Journal of Operational Research, 176*(2), 1185–1204. https://doi.org/10.1016/j.ejor.2005.09.016

Cardoen, B., Demeulemeester, E., & Beliën, J. (2010). Operating room planning and scheduling: A literature review. *European Journal of Operational Research, 201*(3), 921–932. https://doi.org/10.1016/j.ejor.2009.04.011

Cochran, J. K., & Roche, K. T. (2009). A multi-class queuing network analysis methodology for improving hospital emergency department performance. *Computers & Operations Research, 36*(5), 1497–1512. https://doi.org/10.1016/j.cor.2008.02.004

Green, L. V., Soares, J., Giglio, J. F., & Green, R. A. (2006). Using queueing theory to increase the effectiveness of emergency department provider staffing. *Academic Emergency Medicine, 13*(1), 61–68. https://doi.org/10.1197/j.aem.2005.07.034

Günal, M. M., & Pidd, M. (2010). Discrete event simulation for performance modelling in health care: A review of the literature. *Journal of Simulation, 4*(1), 42–51. https://doi.org/10.1057/jos.2009.25

Helbing, D. (2001). Traffic and related self-driven many-particle systems. *Reviews of Modern Physics, 73*(4), 1067–1141. https://doi.org/10.1103/RevModPhys.73.1067

Landa, P., Sonnessa, M., Tànfani, E., & Testi, A. (2021). Discrete-event simulation modelling in healthcare: A comprehensive review. *International Journal of Environmental Research and Public Health, 18*(22), 12262. https://doi.org/10.3390/ijerph182212262

Moosavi, J., Fathollahi-Fard, A. M., & Dulebenets, M. A. (2023). Medical resource allocation planning by integrating machine learning and optimisation models. *Artificial Intelligence in Medicine, 135*, 102456. https://doi.org/10.1016/j.artmed.2022.102456

Santibañez, P., Chow, V. S., French, J., Puterman, M. L., & Tyldesley, S. (2009). Reducing patient wait times and improving resource utilization at British Columbia Cancer Agency's ambulatory care unit through simulation. *Health Care Management Science, 12*(4), 392–407. https://doi.org/10.1007/s10729-009-9103-1

Wu, P. P. Y., & Mengersen, K. (2013). A review of models and model usage scenarios for an airport complex system. *Transportation Research Part A: Policy and Practice, 47*, 124–140. https://doi.org/10.1016/j.tra.2012.10.015

Yu, C., & Liu, J. (2020). Reinforcement learning in healthcare: A survey. *ACM Computing Surveys, 53*(4), 1–36. https://doi.org/10.1145/3394457

Zhang, Y., Zhang, Y., Haghani, A., & Zeng, X. (2018). Time series forecasting of emergency department patient flow. *IEEE Access, 6*, 42946–42956. https://doi.org/10.1109/ACCESS.2018.2861076

Appendix A: Project Timeline

Project Duration: June 20, 2025 - August 29, 2025 (10 weeks remaining)

Completed Work: Literature review, problem formulation, methodology development, and 75% NHS data acquisition

Gantt Chart:

Task	Start Date	End Date	Phase	Duration (days)
Data cleaning, validation, and EDA	23-06-25	29-06-25	1	7
Baseline PTL metrics and dashboard	30-06-25	06-07-25	1	7
M/M/c queue + priority model	07-07-25	13-07-25	2	7
Compare with baseline system	14-07-25	20-07-25	2	7
DES model development in SimPy	14-07-25	27-07-25	3	14
Scenario testing and simulation runs	21-07-25	03-08-25	3	14
Time series forecasting (ARIMA/Prophet)	28-07-25	03-08-25	4	7
RL-based scheduling optimisation	04-08-25	10-08-25	4	7
KPI assessment and comparison	11-08-25	24-08-25	5	14
Final write-up and submission	25-08-25	31-08-25	5	7

Appendix B: Risk Assessment

Risk 1: Data Quality Issues (Likelihood: Medium, Impact: High) NHS administrative data may contain incomplete patient records, inconsistent procedure coding, or missing capacity information across different providers. Poor data quality could delay Phase 1 by 1-2 weeks and fundamentally compromise baseline analysis accuracy, affecting all subsequent modelling phases. Mitigation: Implement early data validation protocols with quality thresholds, develop synthetic data generation capabilities using statistical distributions from validated subsets, and establish collaborative relationships with NHS data custodians for rapid issue resolution.

Risk 2: Model Complexity (Likelihood: Medium, Impact: Medium) Integrating queueing theory, discrete event simulation, and machine learning components presents significant technical challenges that may exceed development capabilities or create models too complex for NHS stakeholders to understand and trust. This could necessitate oversimplification, reducing research impact. Mitigation: Adopt modular design architecture allowing independent component testing, implement phased development with incremental complexity validation, utilise proven stable libraries (SimPy, scikit-learn), and maintain comprehensive documentation with stakeholder-friendly visualisations.

Risk 3: Computational Limitations (Likelihood: Medium, Impact: Medium) Large-scale simulations incorporating thousands of patients, multiple providers, and complex ML optimisation may exceed available computational resources, particularly during intensive scenario testing phases. This could force significant model simplification or extend processing times beyond project deadlines. Mitigation: Secure cloud computing resources (AWS/Azure academic credits), implement parallel processing capabilities for simulation runs, and develop hierarchical modelling approaches that can scale complexity based on available resources.

Risk 4: Forecasting Accuracy (Likelihood: Medium, Impact: Medium) Machine learning demand forecasting models may exhibit poor predictive performance due to healthcare demand volatility, seasonal variations, or insufficient historical data. Forecast errors propagate through optimisation algorithms, potentially undermining the credibility and practical applicability of final recommendations. Mitigation: Implement ensemble forecasting methods combining multiple algorithms (ARIMA, Prophet, neural networks), establish regular cross-validation protocols with rolling windows, and conduct comprehensive sensitivity analysis across multiple demand scenarios.

Risk 5: Timeline Constraints (Likelihood: High, Impact: Medium) The ambitious project scope encompassing five distinct phases within a 10-week timeframe creates significant delivery pressure. Early phase delays could cascade, forcing rushed analysis or incomplete model development that compromises research quality and stakeholder confidence. Mitigation: Establish weekly milestone reviews with clear go/no-go decision points, prioritise core research objectives over advanced features, develop pre-planned contingency scope reduction strategies, and allocate buffer time in critical path activities.