Chronic Patients Scheduling

Tags: Healthcare, Resource allocation, Scheduling.

Category: Agent-Based, Discrete Events, Genetic Algorithms, Optimization, Montecarlo.

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Introduction

The purpose of this article is to share insights on healthcare-related simulation models, particularly in optimizing resource utilization and addressing issues that impact patient health. The model presented is both predictive and prescriptive, providing actionable insights for hospital administrators and healthcare providers.

The target audience includes hospital administrators, simulation engineers, and researchers, but the findings and methodology can be valuable for a broader audience, including healthcare IT professionals and policymakers. The topic is particularly relevant due to the increasing competition among companies offering scheduling ERP solutions, many of which do not fully address the complexity and stochastic nature of optimizing hospital resources for chemotherapy treatment.

Problem statement

Scheduling patients with chronic conditions is a complex task due to the need to manage multiple variables at an individual level. Each patient follows a specific treatment protocol, which includes multiple drugs at different dosages. Additionally, patients may undergo different hospital workflows, where some require drug preparation in advance, while others may have pre-activated processes based on prior blood test results.

A poorly managed scheduling system can lead to excessive patient waiting times, underutilization or overutilization of hospital resources, and critical delays in treatment. In extreme cases, this can result in non-compliance with treatment cycles, severely impacting patient health and survival rates. Traditionally, scheduling decisions are made based on staff experience, which introduces biases and inefficiencies, leading to misallocation of resources and disrupted patient care.

An example of a treatment appointment follows (or not) a structured process:

1. Protocol selection by the doctor.
2. Blood test.
3. Blood test review, either on the appointment day or the day before.
4. Parallel processes:
    a. Patient health control.
    b. Drug order preparation (each drug requires a separate order).
5. Doctor reviews patient health and blood test results.
6. Doctor reviews and modifies drug orders if necessary.
7. Drug orders are approved and activated.
8. Drug preparation in the pharmacy:
    a. Clinical verification.
    b. Blood test and dosage validation.
    c. Labeling and preparation kit assembly.
    d. Drug compounding by pharmacy technicians.
9. Drugs are transported to the treatment center.
10. Nurses administer drugs to patients.
11. Patient is monitored post-administration.
12. Patients are discharged and scheduled for the next session.

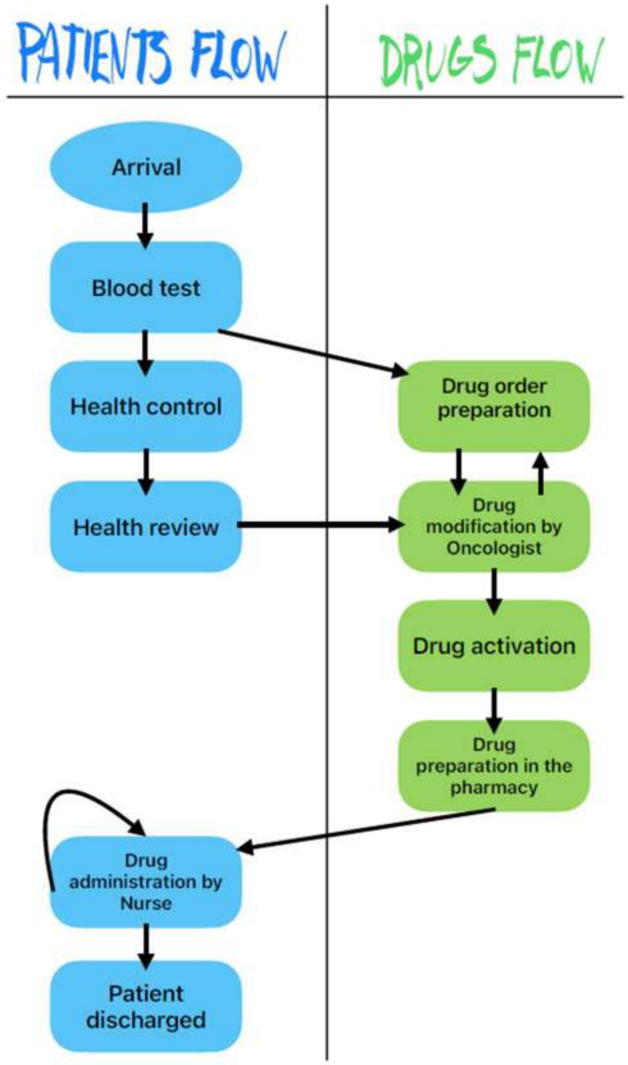


Figure – Example of treatment flow for specific patients

Requirements

The main objectives of the simulation model are:

- To represent the future patient flow based on individual patient variables.
- To evaluate hospital resource utilization in relation to patient and drug-related processes.
- To validate the model using historical data and test various future scenarios, such as different patient loads, appointment schedules, treatment protocols, drug requirements, and hospital staff availability.

Key performance metrics include:

- **Total appointment duration** (total makespan per patient appointment).
- **Total resource overtime usage** (total busy overtime).
- **Total resource utilization time** (total busy time).
- **Total patient waiting time** (time spent waiting between processes during an appointment).
- **Total overtime beyond scheduled shifts** (total overtime hours for hospital resources).

Constrains

Several constraints were considered in the scheduling model:

- Each appointment must be scheduled within a predefined date range (e.g., a patient scheduled for January 10 may have a flexibility window of ±n days).
- Appointments cannot proceed without completing all necessary procedures, meaning that hospital staff must work overtime if necessary.
- Patient arrival times follow a probability distribution, introducing variability that impacts the entire system.
- Each nurse can attend to a limited number of patients per shift and cannot take new patients until an existing one is discharged.
- Each patient follows a personalized sequence of processes during their appointment.

Limitations

Some simplifying assumptions were made in the model:

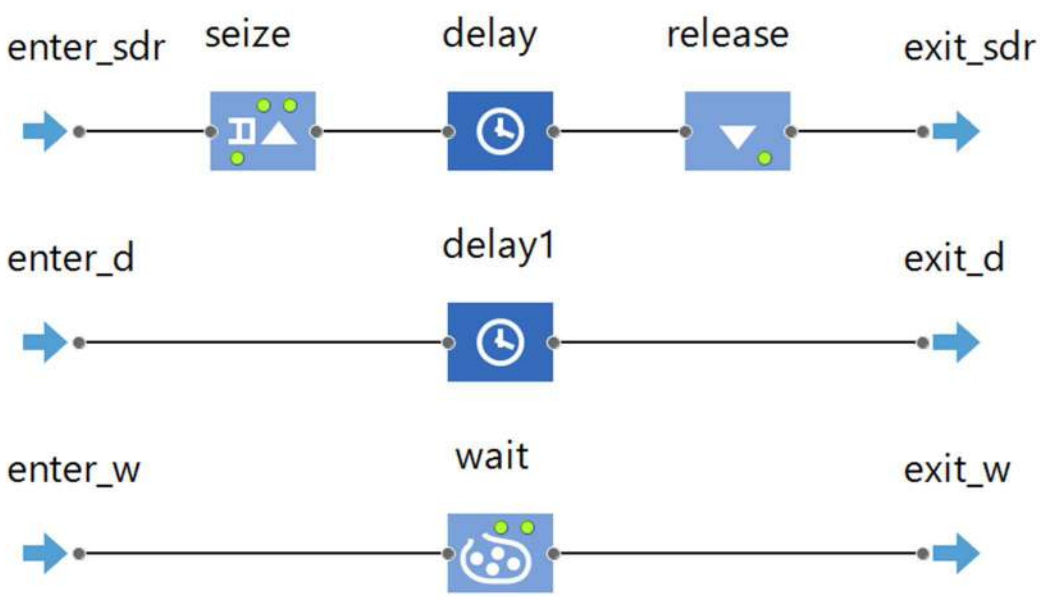
- Equipment failures and maintenance downtimes were not considered; all resources were assumed to be continuously available.
- Patient no-shows were not modeled; it was assumed that all scheduled patients attended their appointments due to the critical nature of chronic illness treatment.

Simulation model

A **multimethod approach** was used, combining **agent-based modeling** (for interactions between resources and patients) and **discrete-event simulation** (for process flows such as patient arrivals, drug administration, and other procedural steps).

Key model components:

- **Model Agent**: Defines the overall simulation process using predefined patient pathways from an external Excel configuration file, allowing dynamic updates easily without reprogramming the Anylogic simulation model.



- **Patient Agent**: Represents individual patients, tracking personal attributes, appointment details, and process flows.
- **DrugBatch Agent**: Represents the specific drugs required for each patient's appointment, running parallel processes for preparation and administration.
- **ResourceAgent**: Represents hospital staff and equipment, including shift schedules and an operational statechart with different states (e.g., idle, busy).

The simulation allows users to:

- Evaluate system performance based on predefined patient loads per shift.

- Modify process sequences and durations for patients and drugs, changing priorities if necessary.
- Customize drug preparation and administration timelines for individual patients.
- Adjust hospital staffing levels per shift dynamically.
- Configure all scheduling parameters via an Excel file effortless, eliminating the need for direct modifications in AnyLogic.

Optimization model

An **evolutionary genetic algorithm** was used to optimize appointment scheduling, minimizing an objective function that balances **total appointment makespan** and **total overtime for resources**. If you'd like to know more about, please check out this video https://www.youtube.com/watch?v=VOEOU3he8rU&ab_channel=NoorjaxConsulting

- **Genetic Algorithm Parameters:**

We used one-point crossover as the recombination method and random resetting as the mutation method. A chromosome in this problem represents the set of appointment dates for all included patients in the experiment. The initial chromosomes in the population are chosen randomly based on the restrictions considered (described later). The crossover percentage determines the number of offspring generated in each generation. The experiment concludes when the maximum number of generations is reached.

- **Constraints in Optimization:**
    - Critical appointments remain fixed.
    - Appointments can only be scheduled within allowed date windows.
    - Time slots (for instance 7 AM or 11 AM) are defined based on visit type.
    - No patient can have more than one appointment per day.

Additionally, a **Monte Carlo experiment** ensures that the optimization results reach a predefined confidence level. Each candidate solution undergoes multiple replications until statistical reliability is achieved.

Results

The optimization experiment incorporated Monte Carlo validation and key optimization parameters to ensure reliable scheduling outcomes. Users receive a **detailed spreadsheet** with:

- The appointment schedule for each patient.
- Confidence intervals validating the statistical robustness of the optimized schedule.
- Insights into scheduling efficiency trends, such as resource utilization patterns and bottlenecks.
- Performance analysis of the optimization process, including convergence rates and computational efficiency.

These results enable hospital administrators to make **data-driven decisions**, ensuring better scheduling efficiency and optimal resource allocation while minimizing operational constraints.

PatientID	Estimated Appointment Date	Appointment Fixed	Optimized Appointment Date
2208	28-03-2025 16:15	False	23-03-2025 19:30
3609	02-03-2025 23:30	True	02-03-2025 23:30
8089	31-03-2025 23:30	False	27-03-2025 22:30
8309	31-03-2025 21:45	False	15-03-2025 22:15
9451	12-03-2025 20:15	True	12-03-2025 20:15
8660	04-03-2025 18:00	True	04-03-2025 18:00
3802	03-03-2025 16:30	False	31-03-2025 20:15
9485	16-03-2025 19:00	False	26-03-2025 16:00
4189	10-03-2025 23:00	True	10-03-2025 23:00
7161	24-03-2025 16:30	True	24-03-2025 16:30

Future/potential work

Future research will focus on enhancing the model to evaluate different resource configurations dynamically. A key improvement would be the development of a decision-support tool that optimizes the number of hospital resources, minimizing both patient-related costs (e.g., waiting times, treatment delays) and operational costs (e.g., staff overtime, drug preparation bottlenecks).

Additionally, incorporating more complex scheduling constraints, such as staff preferences, variable shift durations, and emergency patient arrivals, could further improve the model's applicability. Another avenue for improvement is integrating real-time data feeds from hospital information systems to enable adaptive scheduling adjustments.

Finally, exploring different optimization techniques, such as hybrid metaheuristics or machine learning-assisted scheduling, could enhance both the speed and accuracy of the optimization process.