UNIVERSITY OF OSLO

A Self-Adaptive Digital Twin Architecture for Dynamic Resource Management

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2. Digital Twin Concepts
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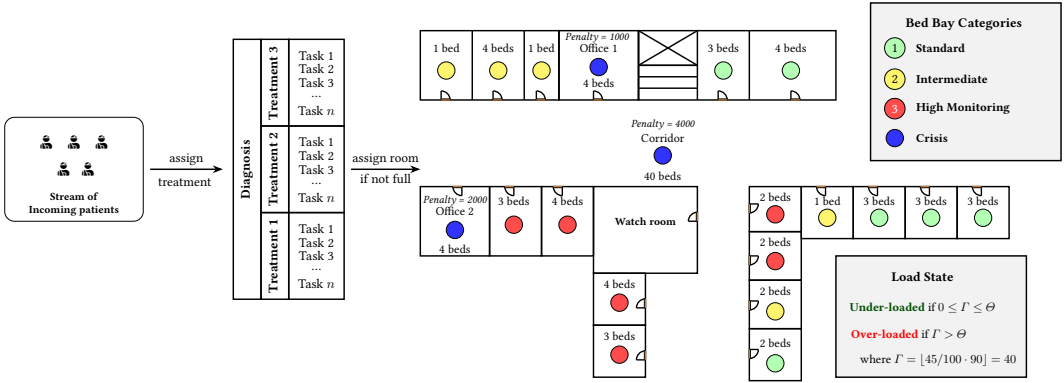
4. Extension to the DT

Why do we need it?



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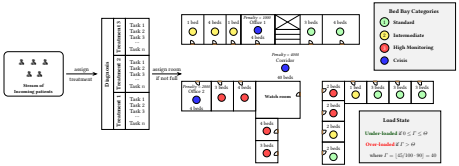

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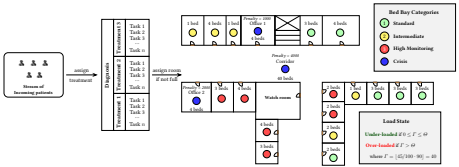

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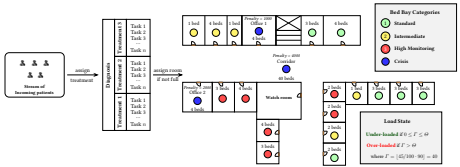

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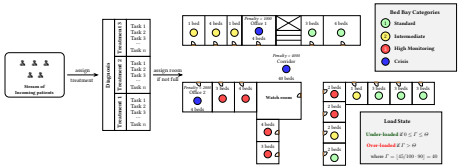

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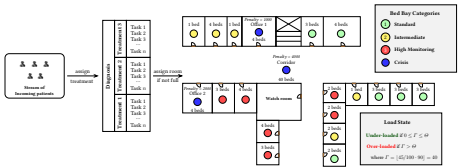

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- We need runtime adaptation with trustworthy model alignment

Baseline: BedreFlyt and the gap

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- It produces bed-bay recommendations for human operators
- Human-in-the-loop actions can diverge from DT suggestions
- **Main gap**: the original ward layout is treated as fixed

What is the goal

Goal: enable the digital twin to reconfigure ward capacity at runtime (open/close spare rooms) in response to changing patient demand, while staying aligned with the real ward and keeping a human in the loop.

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- Human-in-the-loop supervision over the adaptation loop

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   - Modelling aspects
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What is a Digital Twin

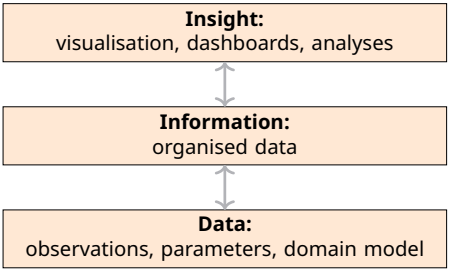
Digital twins are, as defined by NASEM

NASEM Definition of DT (2024)

A digital twin is a set of virtual information constructs that mimics the structure, context, and behaviour of a natural, engineered, or **social system** (or system-of-systems), is dynamically updated with data from its physical twin, has a predictive capability, and **informs decisions** that realise value. The bidirectional interaction between the virtual and the physical is central to the digital twin[a].

[a] National Academies of Sciences, Engineering, and Medicine (NASEM) (2024): Foundational Research Gaps and Future Directions for Digital Twins. The National Academies Press

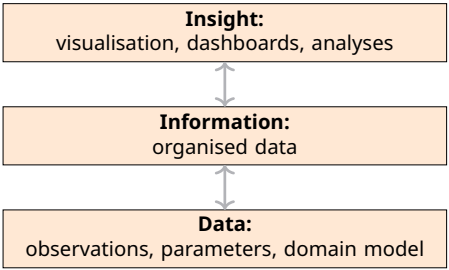
Digital Twins components



Capabilities for different insights:

- **Descriptive:** Insight into the past ("what happened")

Digital Twins components



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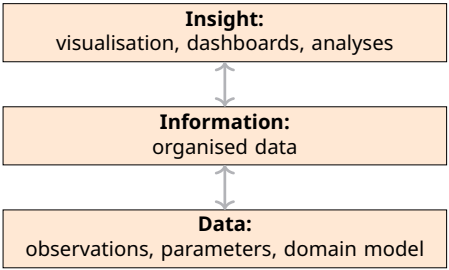

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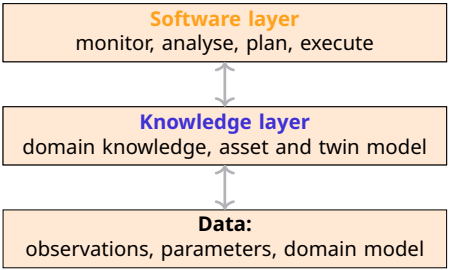

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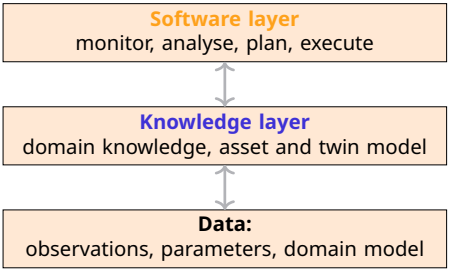

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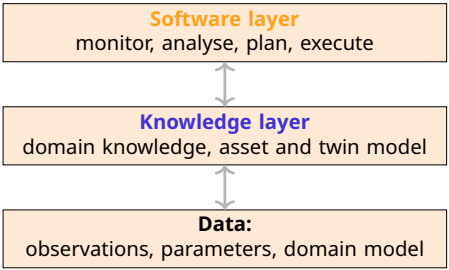

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- States of the DT cycles over time and they need to be captured

Twinning in SMOL

Programming support for twins with a behavioural and a structural layer

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Twinning in SMOL

Programming support for twins with a behavioural and a structural layer

SMOL: Semantic Model Object Language

- Smalll OO programming system
- Ontology reasoners allow querying the KB
- Used to create the digital model

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Twinning in SMOL

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behavioural twins in SMOL

- SMOL can encapsulate (simulation) models based on the FMI standard
- Can automatically adapt the object states in the KB at runtime through semantic lifting

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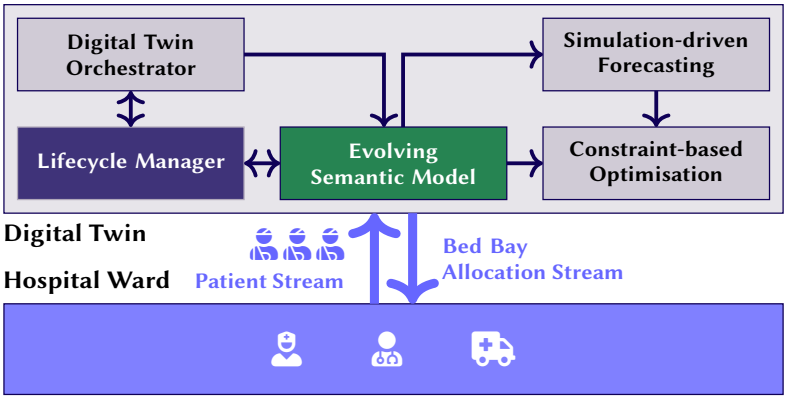
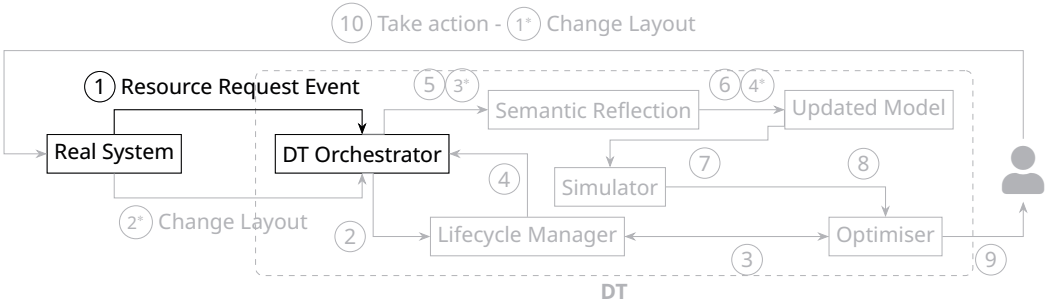
DynResDT: A Self-Adaptive DT Architecture



Human-in-the-loop



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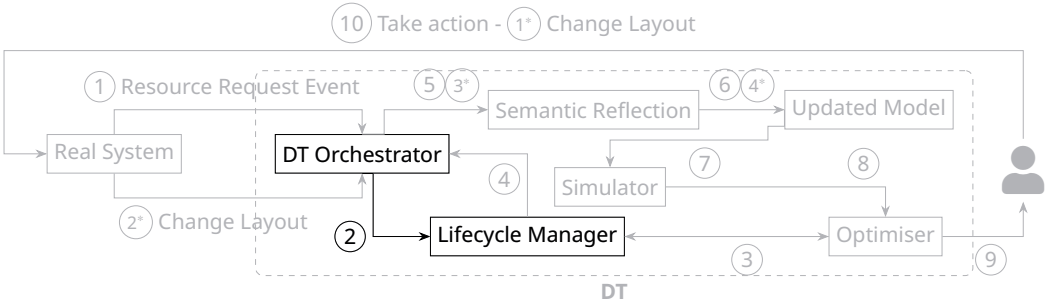

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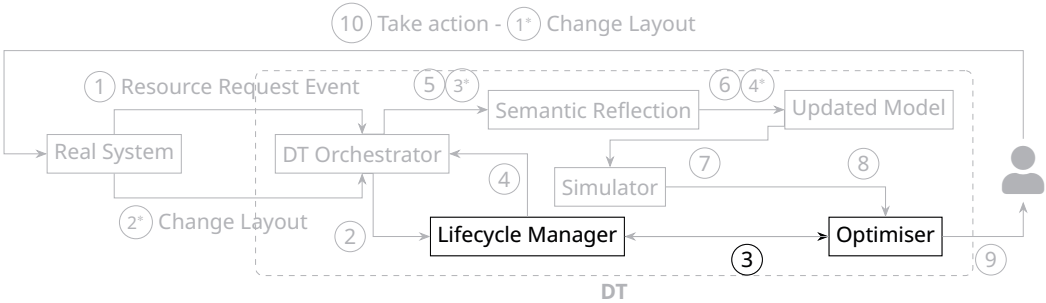

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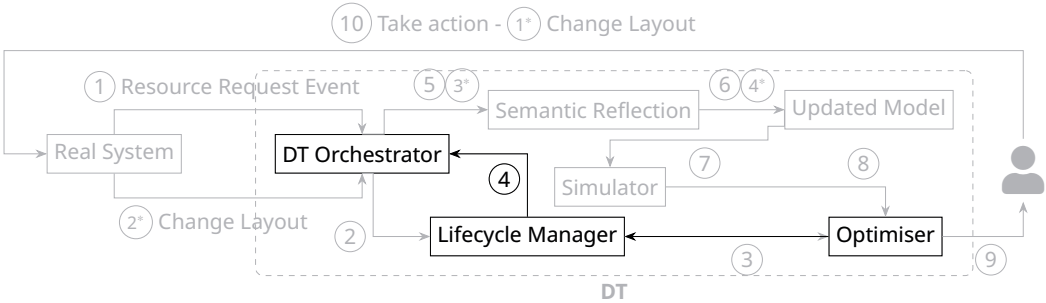

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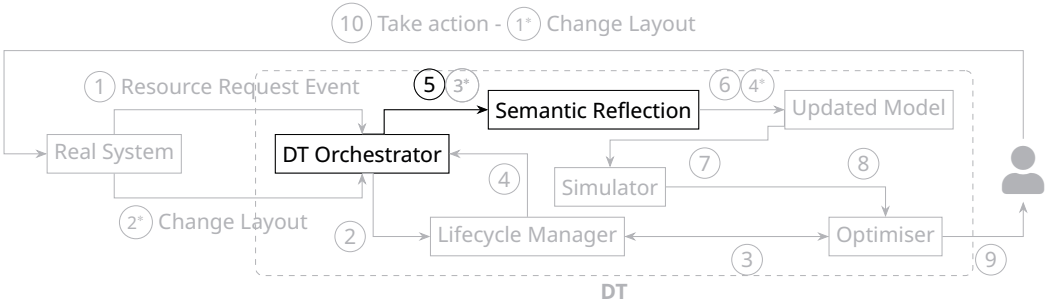

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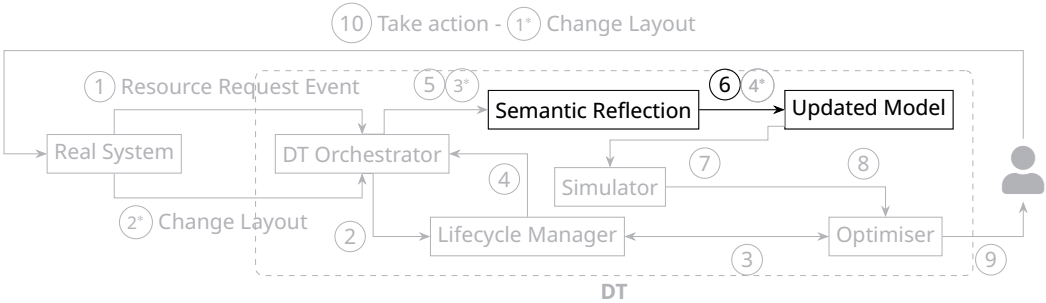

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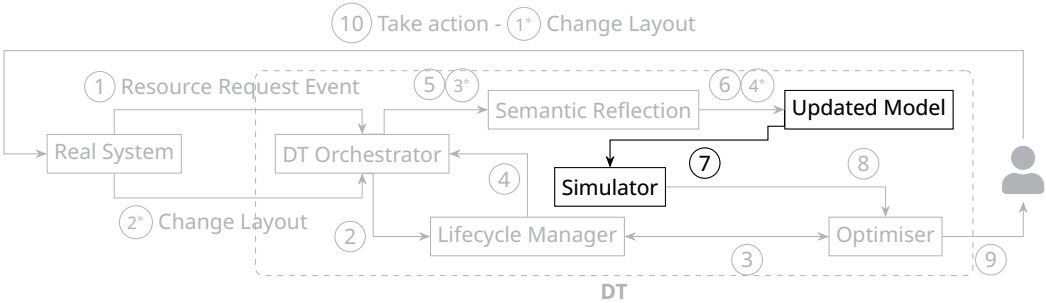

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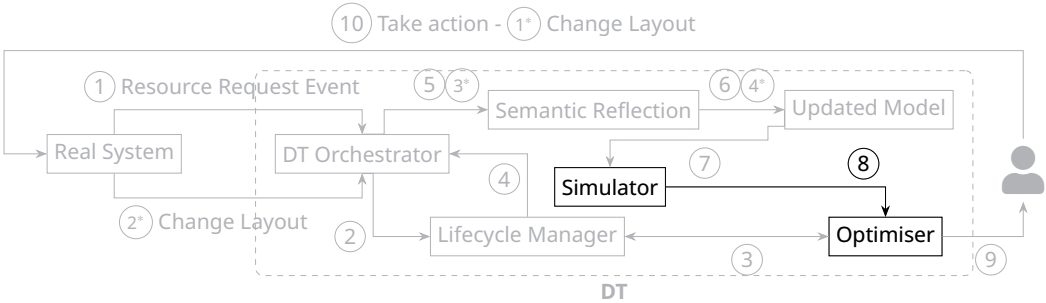

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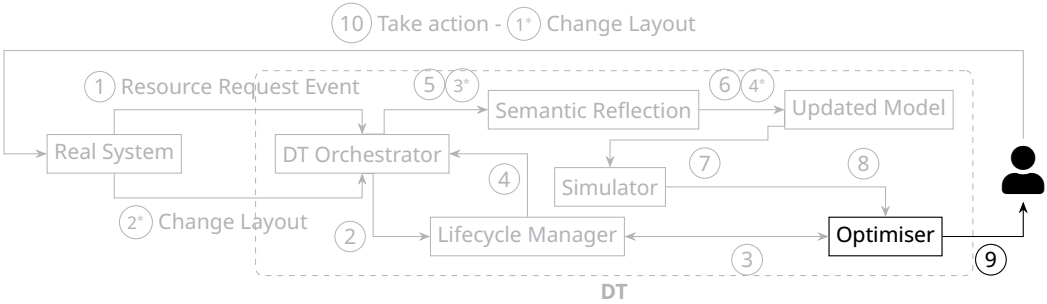

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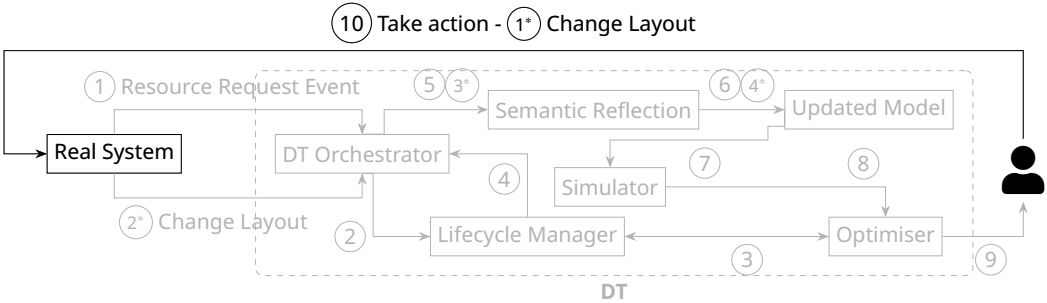

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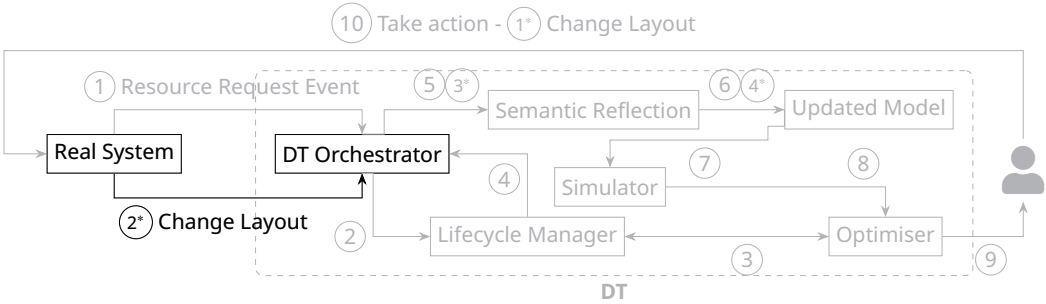

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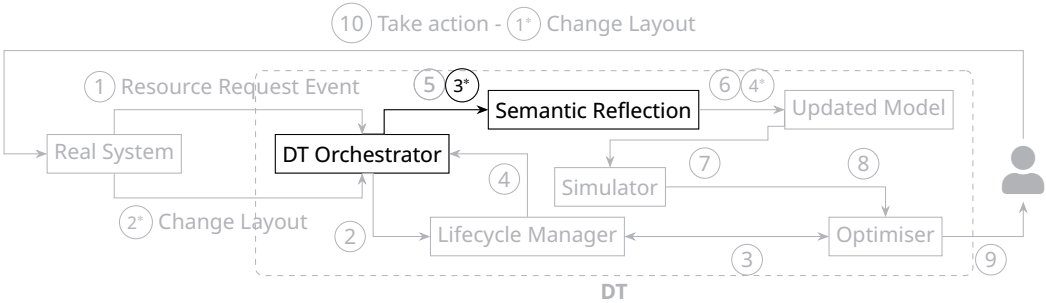

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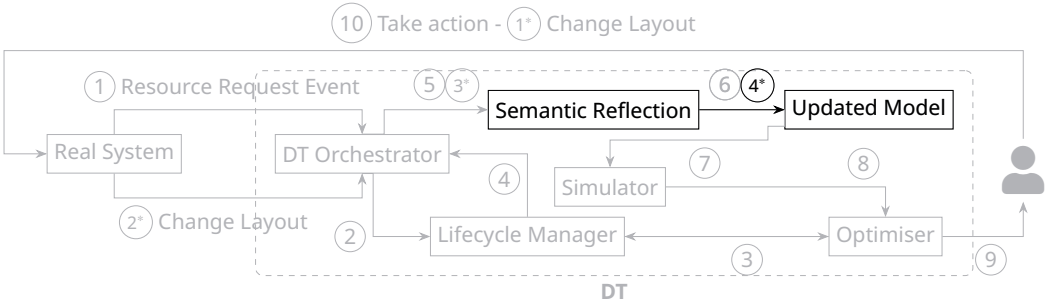

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- Approved actions are reflected back via semantic lifting to maintain alignment
- Semantic reflection re-aligns the runtime model after structural changes
- This enables supervised autonomy: controlled self-adaptation instead of static decision support

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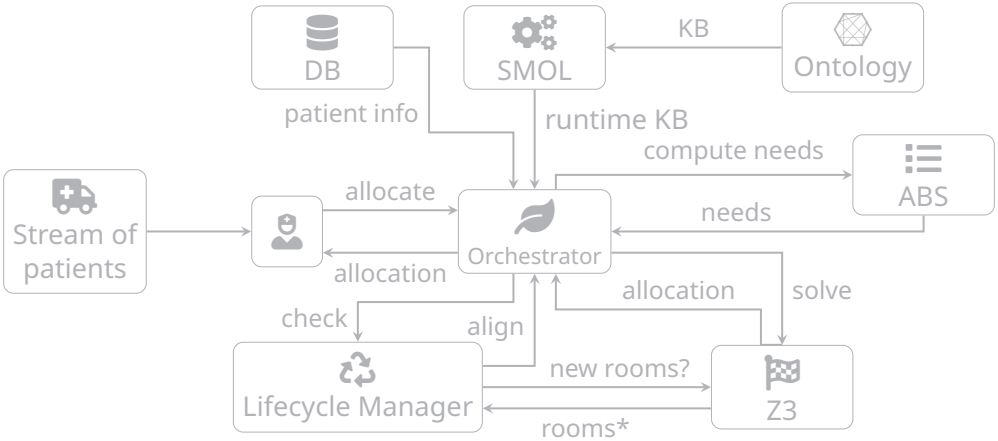
- We allow to account for patient peaks over time, to mimic a period of time of high stress in the ward, switching between high load and low load

Allocation of patients



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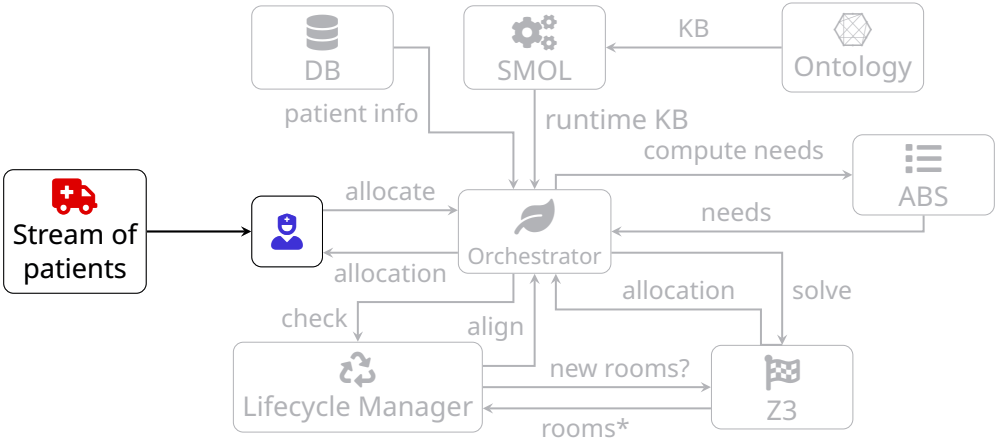

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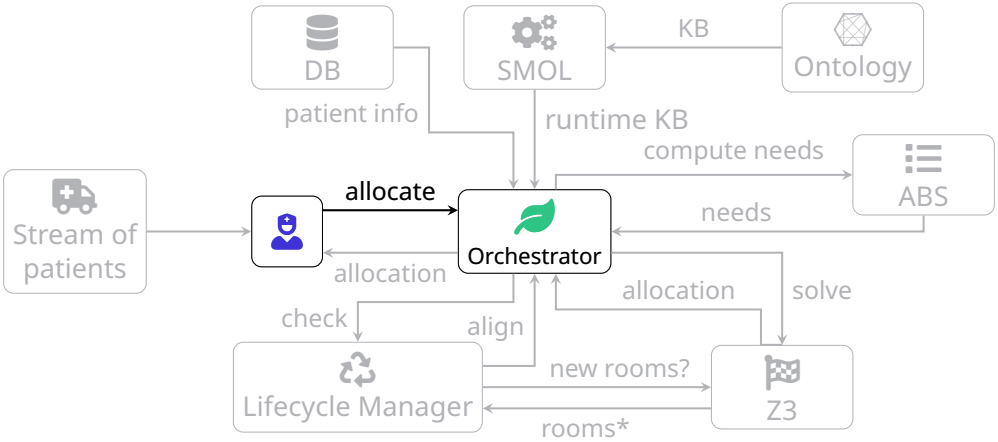

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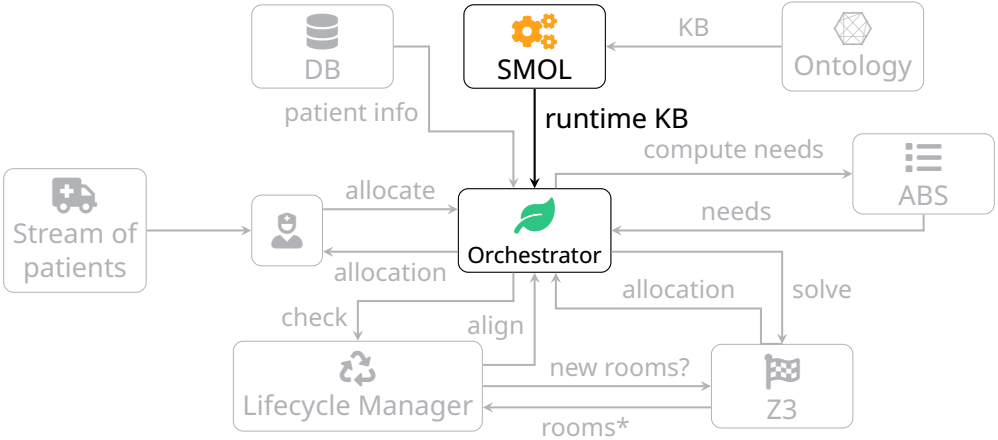

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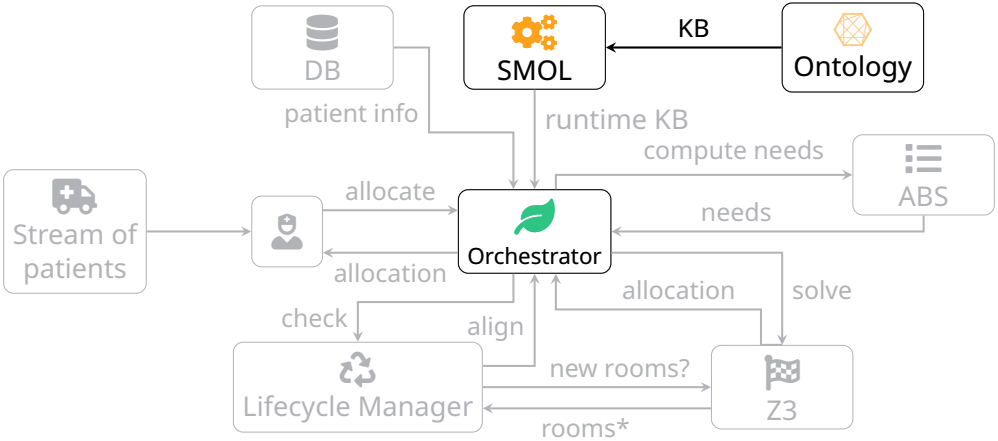

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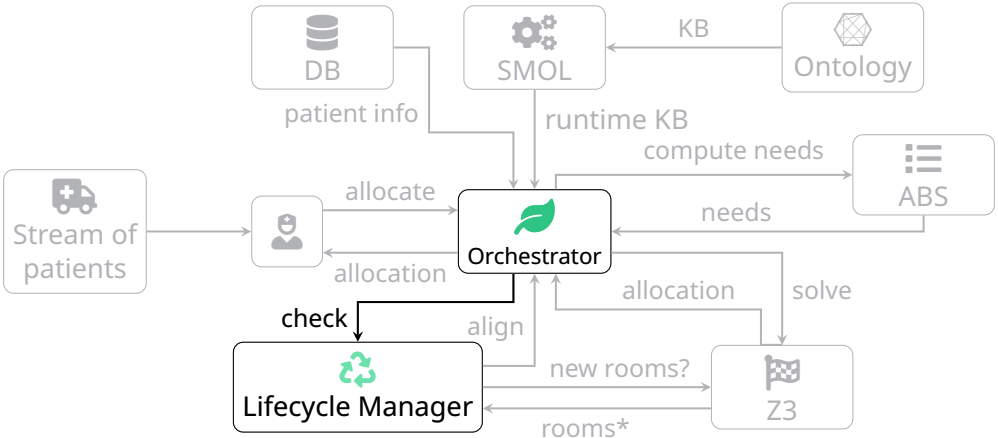

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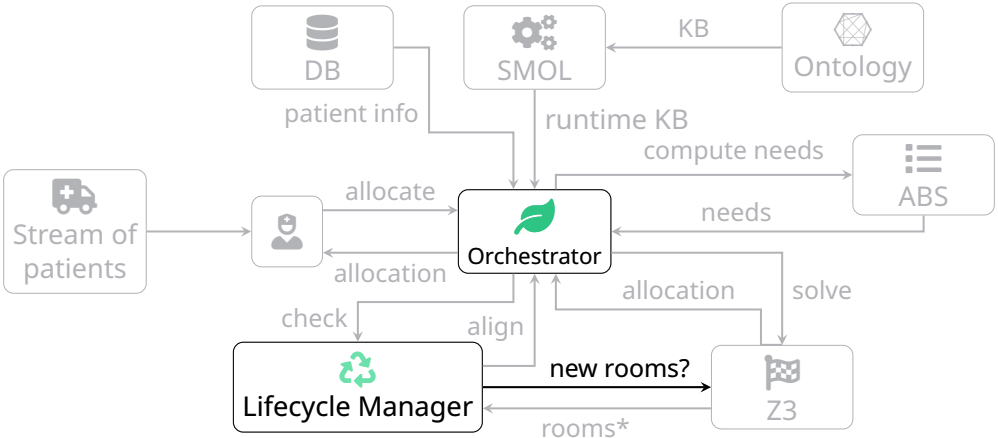

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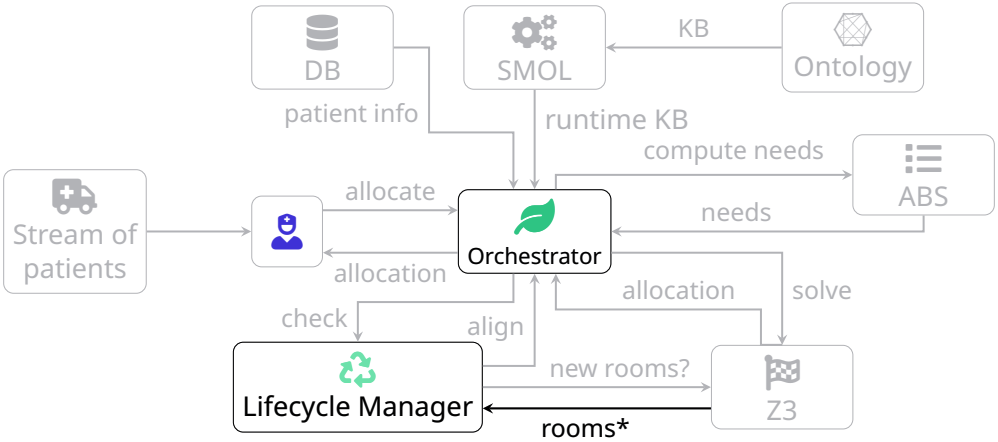

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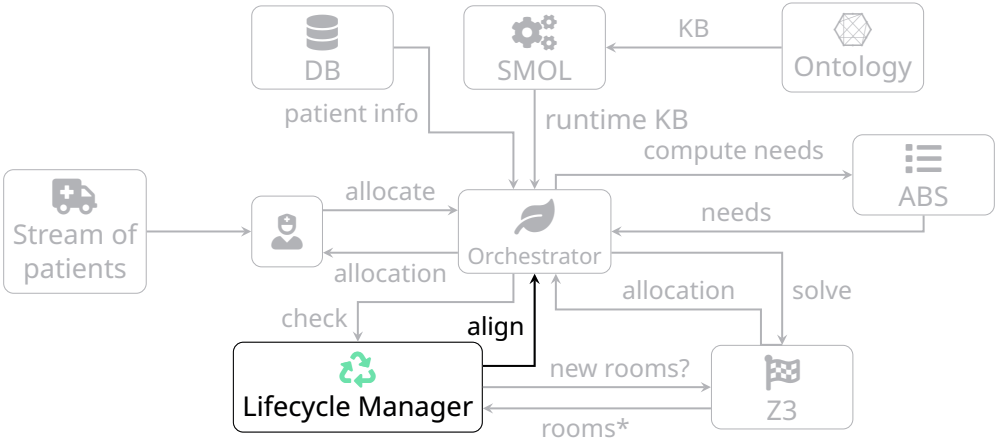

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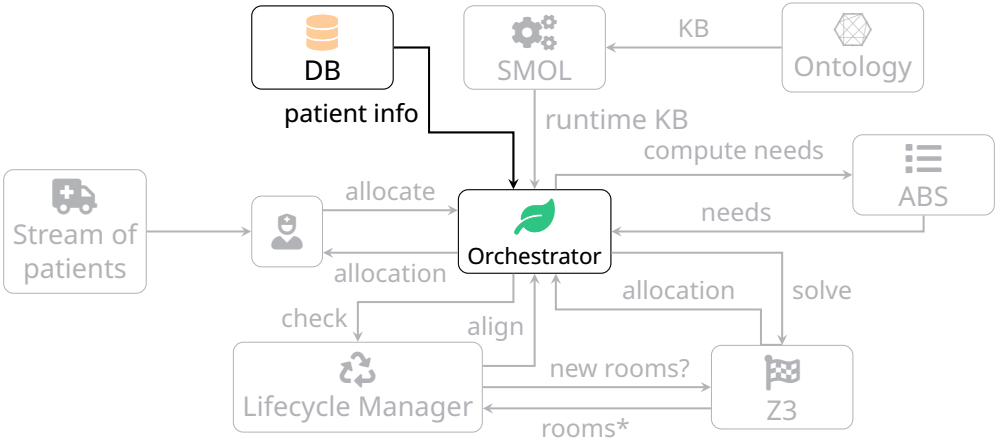

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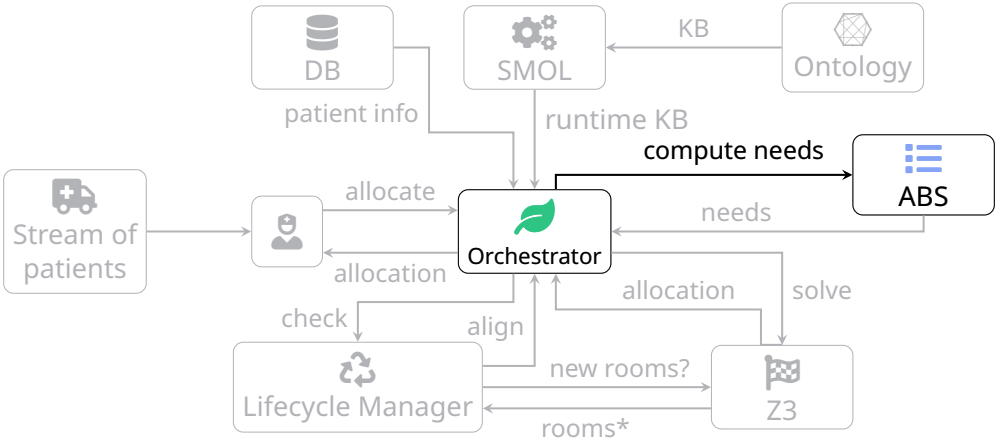

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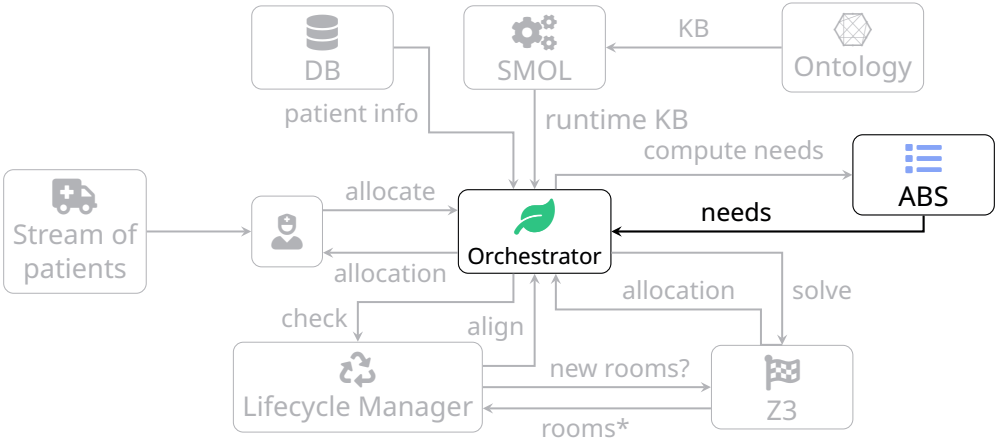

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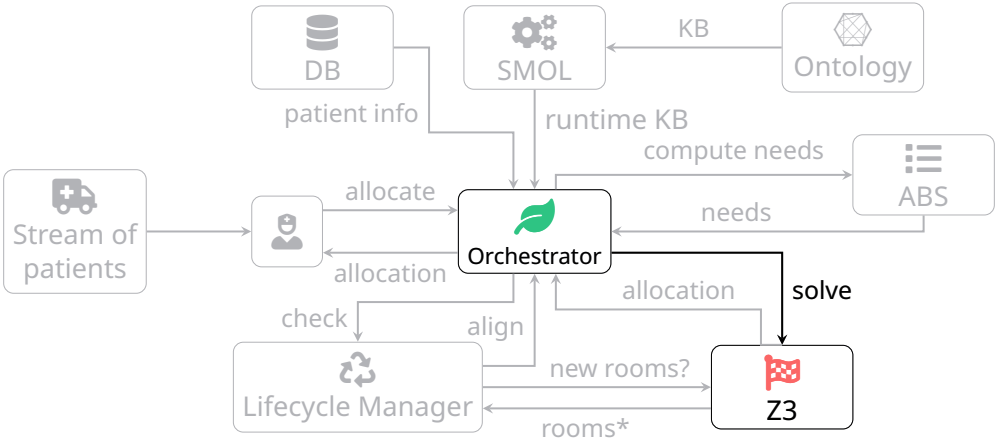

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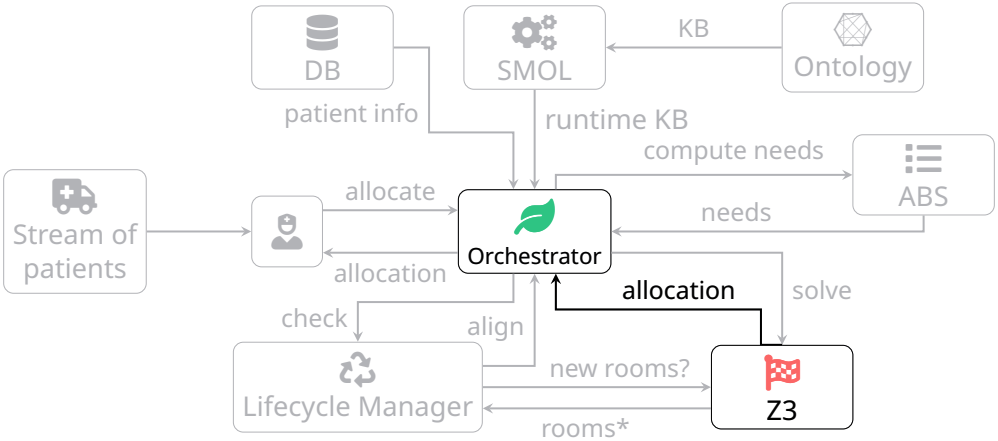

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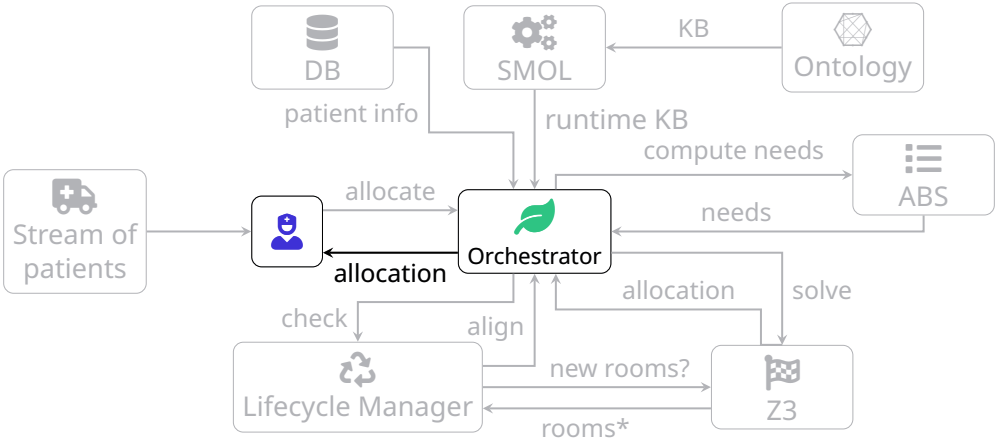
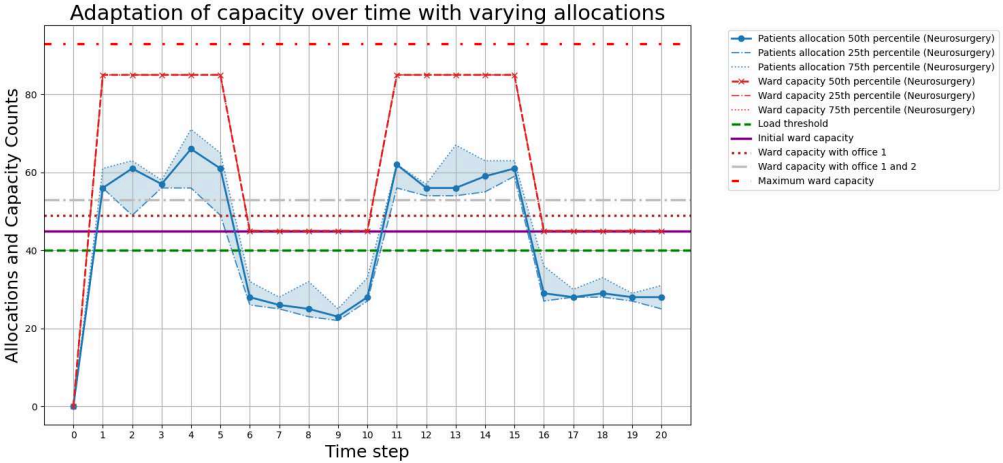


Allocation of patients (cont.)



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- We solve the allocation by solving the constraints with **Z3**

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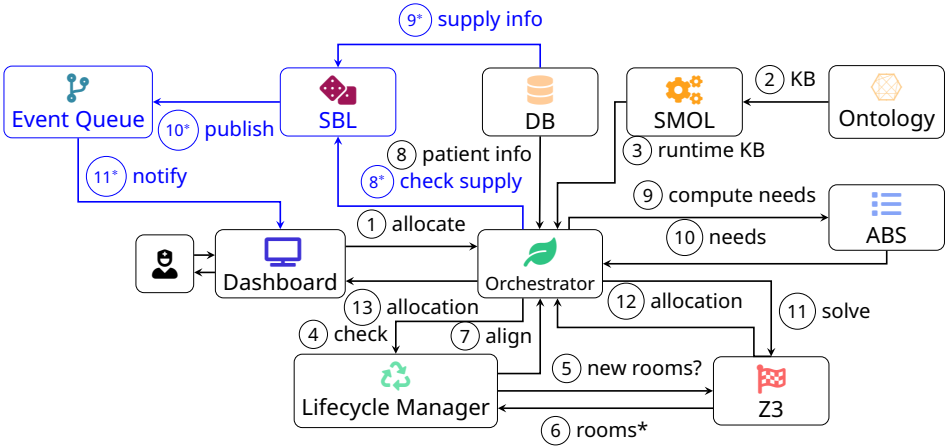
- Cost awareness: penalties encode policy (offices before corridor)
- Trade-off: correctness/alignment vs runtime overhead
- Current limitation: thresholds and penalties are manually tuned

Contents

1. Rationale
2. Digital Twin Concepts
3. Digital Twin Architecture
4. Extension to the DT

Extension to BedreFlyt with SBL



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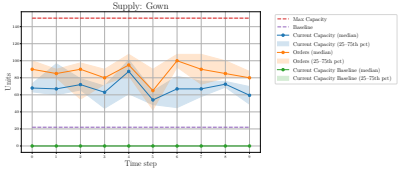
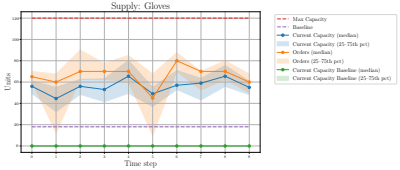
- The human-in-the-loop will then evaluate it and act accordingly

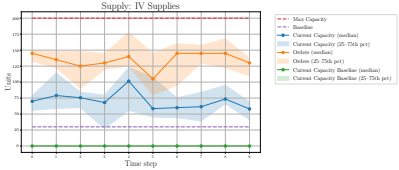
Results of the SBL approach



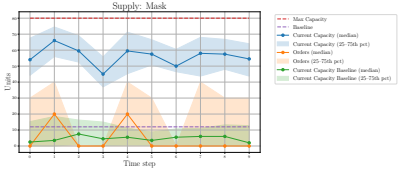
(a) Supply results with baseline for gowns



(b) Supply results with baseline for gloves

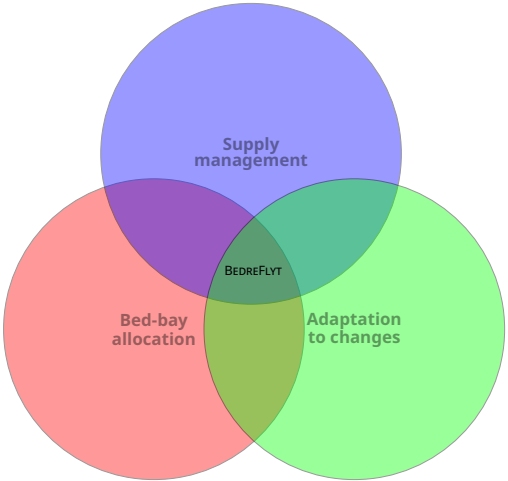


(c) Supply results with baseline for IV supplies



(d) Supply results with baseline for masks

Future directions



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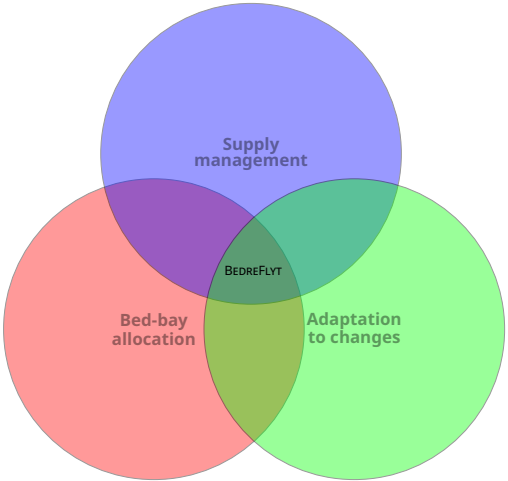

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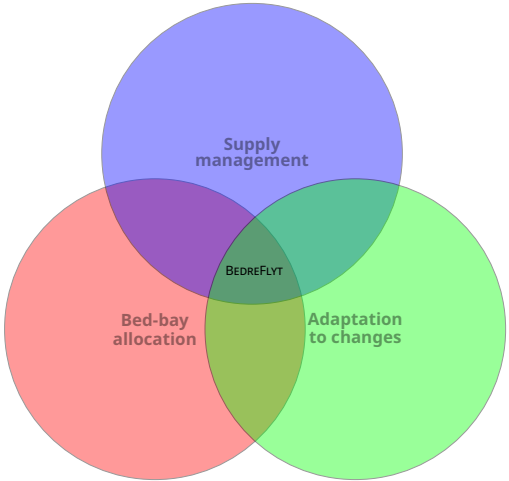

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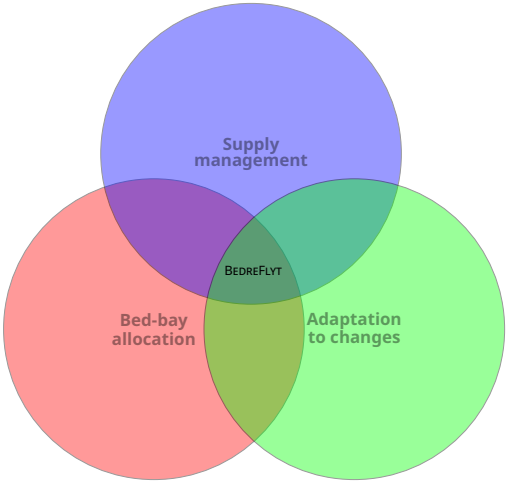

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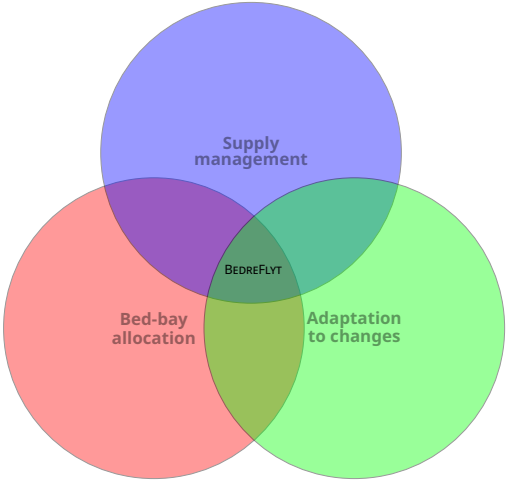
- **Broader scope** (multi-ward, staff constraints, other domains)



Thank you

Riccardo Sieve

riccasi@ifi.uio.no