# Introduction

Production scheduling is a critical process that determines the sequence and allocation of operations and resources in production plants, aiming to optimize efficiency and reduce operational costs. Traditionally, scheduling is performed offline, where static plans are generated in advance based on predicted scenarios and executed by plant operators. However, real-world production environments are inherently dynamic, frequently disrupted by unexpected events such as machine breakdowns, new order arrivals, and uncertainties in processing times and costs. These disruptions often render precomputed schedules impractical or infeasible without timely updates or rescheduling.

To address these challenges, online scheduling systems facilitate a continuous exchange of information between the scheduling system and the production plant’s control system. This enables the real-time adaptation of production plans, ensuring alignment with the latest plant data and maintaining operational flow. Effective online scheduling systems must meet stringent requirements, including real-time responsiveness, modifiability, and predictive accuracy, to adapt to changing conditions while minimizing disruptions to production. Despite advancements in rescheduling methods, many fail to meet industrial expectations, particularly in terms of providing timely responses and generating schedules that are interpretable and executable by plant operators (Henning et al., 2023).

A robust scheduling model must accurately represent the production environment, capturing operational constraints and heuristics in sufficient detail to produce actionable plans with minimal need for manual intervention. Additionally, allowing operators to test and modify schedules based on real-time data is essential for managing unforeseen changes and incorporating tacit knowledge that may not yet be formalized in the scheduling system. Conventional optimization methods, such as mathematical and constraint programming, struggle to meet these demands due to their computational complexity, long solution times, and the challenges of maintaining detailed and flexible models.

Simulation-optimization provides an alternative approach, leveraging high-fidelity simulations to model production processes in detail. These models are inherently flexible and easy to modify, making them suitable for dynamic environments. However, integrating simulation with metaheuristic optimization often results in inefficient search processes, limiting its applicability in real-time scenarios. To overcome these challenges, we employ a rolling horizon evolutionary algorithm (RHEA), a type of evolutionary algorithm designed for real-time decision-making in dynamic environments. RHEA evolves sequences of actions at each decision point, continuously adapting and optimizing solutions based on real-time feedback. Inspired by its success in general video game playing (GVGP), RHEA is tailored for production scheduling to address the unique challenges of industrial processes, emphasizing robustness, responsiveness, and adaptability in the face of real-world disruptions.

This study seeks to answer the following research questions:

Can RHEA, which has proven effective in GVGP scenarios, be successfully adapted for online scheduling in production systems?

What are the key differences in terms of response time, simulation efficiency, and parameter tuning between its application in GVGP and production environments?

How can RHEA be tailored to address the operational constraints and heuristics of real-world industrial settings?

In the broader context, this research contributes to the evolution of Industry 4.0, aligning with the goals of intelligent manufacturing systems. By integrating real-time decision-making capabilities into production scheduling, the proposed methodology supports the development of adaptive, data-driven systems essential for achieving operational excellence. The flexibility and maintainability of the simulation-optimization framework make it an accessible and scalable tool for diverse industries, paving the way for the widespread adoption of intelligent scheduling systems capable of addressing the complexities of modern production.

To validate our approach, we apply it to a pharmaceutical batch production case study involving a multiproduct, multistage plant. The case study features complex constraints such as machine eligibility and sequence-dependent changeovers. We compare our results against an idealized "clairvoyant scheduler" with perfect knowledge of future events, demonstrating that our method performs competitively under time constraints while effectively managing unforeseen disruptions.

The remainder of this paper is structured as follows:

Section 2 reviews related work and provides the theoretical foundations for online scheduling and RHEA. Section 3 describes the proposed methodology, including the integration of RHEA with simulation-optimization and the details of the pharmaceutical batch production case study. Section 4 presents the results and discusses the performance of the proposed approach in terms of response time, adaptability, and scheduling quality. Finally, Section 5 concludes the paper, summarizing the findings and outlining future research directions.

# Introduction (Dense)

Production scheduling is a decision-making process that determines the sequence and allocation of operations and resources in production plants, aiming to optimize efficiency and reduce operational costs. Traditionally, scheduling is performed offline, where static plans are generated in advance and executed by plant operators. However, real-world production environments are inherently dynamic, frequently disrupted by unexpected events such as machine breakdowns, new order arrivals, and uncertainties in processing times and costs. These disruptions often render precomputed schedules impractical or infeasible without timely updates or rescheduling.

To address these challenges, online scheduling systems enable real-time adaptation of production plans by maintaining a continuous exchange of information between the scheduling system and the production plant’s control system. Effective online scheduling must meet stringent requirements, including real-time responsiveness, modifiability, and predictive accuracy, to maintain alignment with the latest plant data while minimizing disruptions. Despite advancements, many existing approaches fall short in delivering timely responses and generating schedules that are interpretable and executable by plant operators (Henning et al., 2023).

Simulation-optimization offers an alternative to conventional methods by leveraging high-fidelity simulations to model production processes in detail. These models are flexible and easy to modify, making them well-suited for dynamic environments. However, coupling simulation with metaheuristics often results in inefficient search processes, limiting its applicability in real-time scenarios. To overcome these challenges, this study employs a rolling horizon evolutionary algorithm (RHEA), a type of evolutionary algorithm designed for real-time decision-making in dynamic environments. RHEA evolves sequences of actions at each decision point, continuously optimizing solutions based on real-time feedback. Inspired by its success in general video game playing (GVGP), RHEA is adapted to handle the unique demands of production scheduling, emphasizing robustness and adaptability in the face of real-world disruptions.

Simulation-optimization uses detailed simulation models to optimize real-world scheduling problems. The model can handle complex systems with problem specific special cases, heuristics, and exceptions. Due to the high fidelity of the model more accurate predictions of the production process can be generated and therefore more accurate decisions can be deduced. The need to adjust the decisions because they do not reflect the real plant is also minimized. However, simulation-optization methods are not sample efficient and there is a clear tradeoff between computational time and solution quality.

On the other hand, for rigorous models it is difficult to represent all features of a plant, especially, when there a special cases and plant specific heuristics, e.g., complex conditions and constraints that heuristically manage the discharging of tanks, or detailed representations of shift schedules and logistics. Complex models also tend to have large computational time and often decomposition approaches are needed to find suboptimal solutions fast and their maintenance needs expert knowledge.

**We see many benefits of the simulation optimization framework. However there are also some challenges like for example the tradeoff between computation time and solution quality. The framework also has to be able to handle disruptions and uncertainties and regularly exchange information with the production system to run with the newest information.**

**Therefore our paper tries to answer the question of how to bring simulation-optimization to a real plant. Our hypothesis is that simulation optimization can be used in a reactive real-time scheduling system. We borrow ideas from rolling horizon evolutionary algorithms for general video game playing and discuss which modifications are necessary to use this approach in our study.**

This study investigates the following research questions:

Can RHEA, proven effective in GVGP scenarios, be successfully adapted for online scheduling in production systems?

What are the key differences in terms of response time, simulation efficiency, and parameter tuning between its application in GVGP and production environments?

How can RHEA be tailored to address the operational constraints and heuristics of real-world industrial settings?

In a broader context, this research contributes to Industry 4.0 by supporting the development of intelligent manufacturing systems. Integrating real-time decision-making capabilities into production scheduling enables adaptive, data-driven systems essential for achieving operational excellence. The flexibility and maintainability of the simulation-optimization framework make it a scalable and accessible tool for diverse industries, paving the way for widespread adoption of intelligent scheduling solutions.

To validate our approach, we apply it to a pharmaceutical batch production case study involving a multiproduct, multistage plant. The case study features complex constraints such as machine eligibility and sequence-dependent changeovers. We compare our results against an idealized "clairvoyant scheduler" with perfect knowledge of future events, demonstrating that our method performs competitively under time constraints while effectively managing unforeseen disruptions.

The remainder of this paper is structured as follows:

Section 2 reviews related work and theoretical foundations for online scheduling and RHEA. Section 3 describes the methodology, including the integration of RHEA with simulation-optimization and the pharmaceutical batch production case study. Section 4 presents results, focusing on performance metrics such as response time, adaptability, and scheduling quality. Finally, Section 5 concludes with a summary of findings and future research directions.

Research question:

How to bring simulation-optimization to a real plant

* Schedules may become infeasible if disruptions occur
* Minor disruptions that have a small impact on the schedule
* Major disruptions that may lead to infeasiblity

Hypothesis:

Continuous improvement of schedules in a real-time simulation-optimization framework

* A regular update of the model parameters and optimization instance with the plant states
* The optimization runs continuously in between update
* The model

# Approach

Simulation-Optimization

* Scheduling system
  + Discrete-event simulation that represents the production plant
  + Evolutionary algorithm that generates scheduling decisions that are evaluated by the simulation model
  + The Simulation models sends back the objective values
  + The EA allows for massive parallel evaluation
  + The degrees of freedom are the allocation of orders to units
  + The sequencing of orders
* Simulation-optimization with discrete-event simulations and evolutionary algorithms
* The model represent the production environment in high fidelity
  + Plant heuristics
  + Operations
  + Resources
* Simulation model provides
  + Detailed schedules
  + Assessment of the current state
  + Visualizations of the schedules
* The EA generates decisions that are evaluated by the simulation model

Simulation-optimization for real plants

* Handle minor and major disruptions and uncertainties
* Responsiveness
* Continuous improvements of schedules
* The EA runs continuously
* Model parameters and degrees of freedom of the EA are updated periodically, e.g., when the state of the plant changes, and event-driven, when disruptions occur
* Updates of the degrees of freedom if the problem structure changes due to
  + Decisions have been executed in the plant and are no degrees of freedom anymore
  + Disruptive events occur
  + Parameter uncertainties that change the real schedule
* Continuous generation of new schedules

Interaction with the production plant

* Scheduling system
  + Consists of the Evolutionary algorithm and the discrete-event simulation
  + Runs the evolutionary algorithms and generates decisions
  + Receives update triggers from the control center as well as updates on the state of the real plant
  + Receives the current plant states
  + Modifies the degrees of freedom of the evolutionary algorithm, e.g., the genotypes
  + Initializes the evolutionary algorithm efficiently with the last population
  + Updates the parameters of the discrete event simulation
    - Decodes the genomes
    - Evaluates the schedules
  + Updates and modifies the simulation-optimization framework
* Production system
  + Consists of the Control Center and the Production facility
  + Control center receives plant data and processes it into plant states
  + Starts the EA
    - Plant states are send to the scheduling system
    - Parametrizes the EA
    - Triggers updates
      * Periodic due to synchronization of the scheduling system and the production system
      * Reactive due to unforeseen events
  + Sends decisions to the production plant
  + Scheduling system sends decisions and predictions to the control center
  + Production plant
    - Executes schedules
    - Generates plant data

# Approach

Our reactive real-time scheduling system integrates simulation-optimization with real-time feedback to generate adaptive and efficient production schedules. The system is designed to handle the complexities of dynamic industrial environments, providing continuous improvements while responding to disruptions and uncertainties. The following describes the core components of the system and their interactions.

The scheduling system is built upon a simulation-optimization framework that combines a high-fidelity discrete-event simulation (DES) with a tailored evolutionary algorithm (EA). The DES represents the production plant in detail, incorporating operational constraints, resource availability, and plant heuristics. This model provides a realistic evaluation of scheduling decisions, producing objective values and detailed visualizations of schedules to facilitate the assessment of the current state. The EA generates scheduling decisions by optimizing two primary degrees of freedom: the allocation of orders to resources and the sequencing of operations. By iteratively refining its decisions based on feedback from the simulation, the EA enables massive parallel evaluations, significantly accelerating the search process.

This integration of DES and EA ensures that the scheduling model aligns closely with real-world production conditions. The simulation provides detailed, executable schedules while the evolutionary algorithm explores optimal solutions, addressing the inherent trade-offs between efficiency and adaptability.

The system is uniquely designed to accommodate the dynamic nature of production environments. It continuously generates and improves schedules, ensuring responsiveness to both minor and major disruptions. Periodic updates, triggered by scheduled synchronization events, ensure that the scheduling model reflects the current plant state. Additionally, reactive updates handle unforeseen events, such as equipment failures or unexpected order arrivals, by modifying the simulation model and adjusting the degrees of freedom within the EA. For example, decisions that have already been executed in the plant are removed from the decision space, while new constraints introduced by disruptions are incorporated into the model.

To maintain responsiveness, the EA operates continuously, producing updated schedules as new data becomes available. This allows the system to quickly adapt to uncertainties, such as deviations in processing times or resource availability, ensuring minimal disruption to plant operations. Furthermore, the simulation model dynamically adjusts parameters to reflect the real-time state of the plant, enabling the scheduling system to remain synchronized with the production facility.

Interaction between the scheduling system and the production plant is central to the system’s functionality. The scheduling system consists of the EA and the DES, which work together to generate, evaluate, and refine schedules. It receives updated plant states and disruption notifications from the control center, which processes raw plant data collected from the production facility. These updates trigger modifications to the simulation model and the EA, such as initializing the algorithm with the latest population and adjusting genotypes to reflect changes in the problem structure. For instance, the system may update task sequences, reallocate resources, or modify parameters in the simulation to address new constraints introduced by disruptions.

The production system includes the control center and the production facility. The control center collects plant data, processes it into actionable plant states, and sends these updates to the scheduling system. Synchronization between the two systems occurs periodically, ensuring alignment between the scheduling model and the production plant. Reactive updates are triggered by unforeseen events, allowing the system to address disruptions in real time. Scheduling decisions generated by the EA and evaluated by the DES are relayed to the production facility, where they are executed. Plant data generated during execution is sent back to the control center, creating a continuous feedback loop that drives ongoing improvements.

This real-time feedback loop forms the foundation of the system’s adaptability. The scheduling system continuously refines its decisions based on the latest data, providing the production plant with actionable schedules that are both robust and responsive. By integrating high-fidelity simulation with a powerful evolutionary algorithm, the system bridges the gap between planning and execution, ensuring efficient and dynamic scheduling for complex industrial environments.