Evolutionary Algorithm-Based Real-Time Scheduling via Simulation-Optimization

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Introduction & Motivation

INOSIM

- **INOSIM Insight**: Discrete-Event Simulator for the process industry.
- **INOSIM Foresight**: Real-time decision support system that initializes from the OT-System.

Scheduling in the process industry

- **Disruptions:** minor (timing shifts, delays, etc.) vs. major (rush orders, maintenance, failures) can cause suboptimal or infeasible plans.
- **Offline vs. online:** Schedules may become suboptimal or infeasible if disruptions occur [1]; Online scheduling reacts to real-time plant data and events.

Simulation-Optimization (SO)

- **High-fidelity discrete-event simulation:** The simulator both evaluates and *constructs* feasible schedules.
- **Optimization on the real process:** The search runs directly on the Discrete-Event Simulator model, such that complex constraints and side-effects that are hard to capture in rigorous methods are naturally respected.
- **Implementable schedules:** The gap between simulated and actual behavior is small, so operators can follow the schedule without major manual modifications.

Evolutionary Algorithm (EA)

- **Population based metaheuristic:** Stochastic search and improvement of candidate solutions
- **Works with complex, black-box simulators:** They can handle intricate logic and constraints without explicit models or gradients.
- **Anytime performance for real-time decisions:** Produces a "best-so-far" schedule at any moment, that returns a usable plan for each update.
- **Population continuity across replans:** The population can be carried over and repaired after disturbances to reuse good patterns and adapt the schedule.

Reactive real-time scheduling framework [2]

Continuous Improvement

- The EA runs continuously with a receding horizon
- The scheduling system provides a feasible solution at each time point (e.g., t_{update})
- **Fast, reliable adaptation after disturbances:** After each update, SO quickly re-simulates candidate schedules under the current state, producing realistic plans that can be applied almost directly, which shortens recovery time after rush orders, maintenance, or delays.

Update Events

- Periodic updates at fixed time points and event-driven updates after major disruptions
- Reinitialization of the problem at update events
- Continuous generation of new schedules at response events $t_{response}$

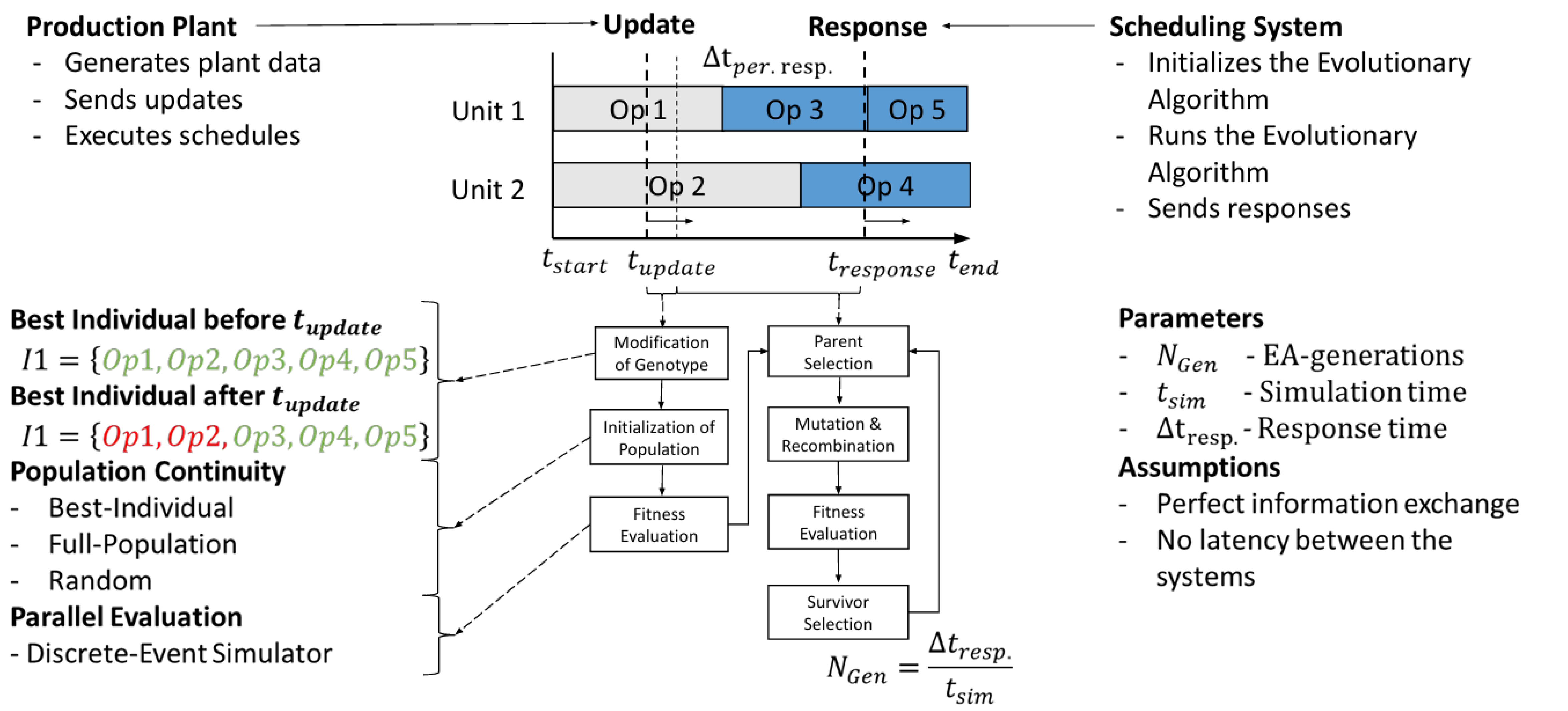

Figure 1: Real-time Scheduling via Simulation-Optimization

Results & Conclusion

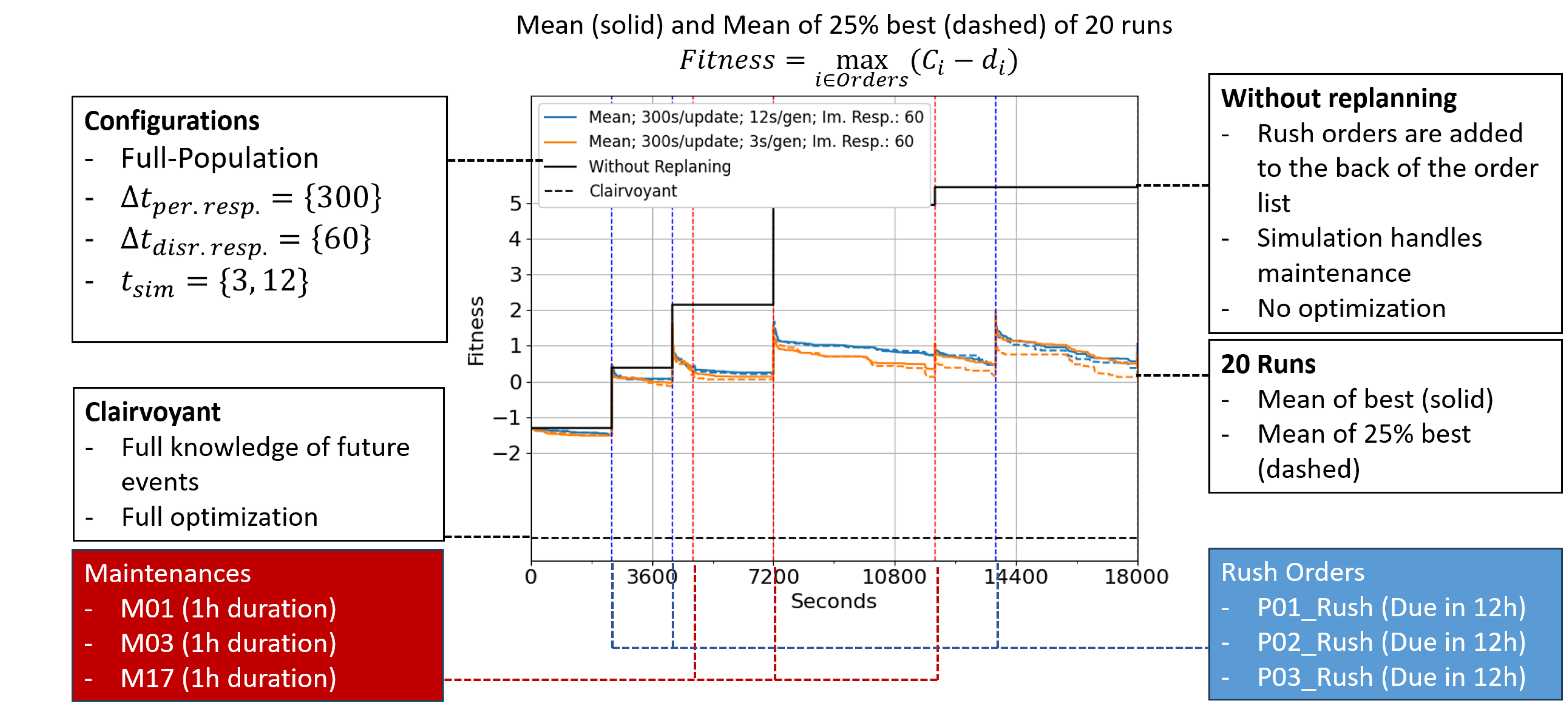

Figure 2: Rolling horizon scheduling with evolutionary algorithms and discrete event simulations. Maintenances and rush orders are introduced at different times.

Case Study

- Large batch scheduling problem
- Multi-stage and multi-product plant
- Eligibility constraints and changeovers
- 6 stages with 2 or 3 units and 30 product types

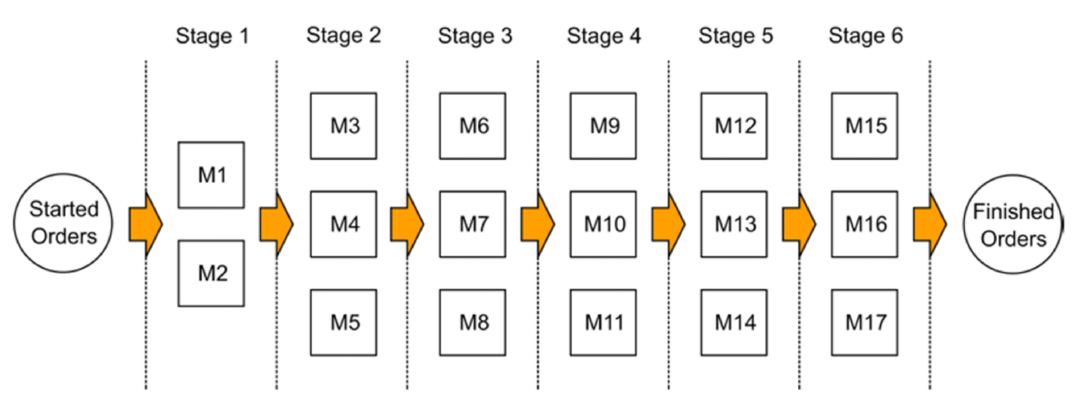

Figure 3: Plant layout

Degrees of Freedom

- Sequence of orders
- The simulation handles the allocation heuristically

Problem Instance

- 30 Orders
- 3 rush orders and 5 maintenances
- **Objective:** Min. Tardiness
  $F = \min(C_i - d_i)$
  $C_i =$ **Completion Time**
  $d_i =$ **Due Date**

Conclusion

- A new approach on how to use simulation-optimization for real-time scheduling
- Continuously improve the schedules with an evolutionary algorithm
- React to disruptive events and provide a feasible solution at any time

Table: Comparison of simulation configurations and performance metrics.

t_{sim}	$\Delta t_{per.\ resp.}$	$N_{per.\ gen.}$	$\Delta t_{dyn.\ resp.}$	$N_{dyn.\ gen.}$	**Mean of best**	**Mean of best 25%**
12	300	25	60	5	-0.20	-0.74
12	300	25	12	1	-0.32	-0.96
12	60	5	60	5	-0.52	-1.08
12	60	5	12	1	-0.23	-0.74
3	**300**	**100**	**60**	**20**	**-0.81**	**-1.60**
3	300	100	3	1	-0.61	-1.14
3	60	20	60	20	-0.68	-1.34
3	60	20	3	1	-0.24	-0.83
Clairvoyant					**-4.37**	**-4.37**
W/o Replan					**5.44**	**5.44**

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Process Dynamics and Operations Group

References

[1] F. Espinaco and P. Henning, "Industrial Rescheduling Approaches: Where Are We and What is Missing?" Production Research – Americas , pp 461–467 (2023).
[2] E. Pasieka and S. Engell, "Evolutionary Algorithm Based Real-time Scheduling via Simulation-Optimization for Multiproduct Batch Plants", ESCAPE 35, July 2025.