Systems & Control Transactions

Original Research Article
Peer Reviewed Conference Proceeding
ESCAPE 36 - European Symposium on Computer Aided Process Engineering
Sheffield, UK. 21-24 June 2026

PSE PRESS

A framework for dynamic rescheduling under disruptions and resource constraints

David Robins[a], Farshid Babaei[a], Joan Cordiner[a], and Solomon F. Brown[a]*

[a] The University of Sheffield, School of Chemical, Material, and Biological Engineering, Sheffield, United Kingdom
* Corresponding Author: S.F.Brown@sheffield.ac.uk

ABSTRACT

Manufacturing disruptions can be a major driving factor in the wastage of resources and delays which result in spiralling costs and cancelled orders. Operational decision making should therefore consider the potential for disruptions from as many sources as possible, encouraging improvements to operational resilience and agility. Our work presents a scheduling and rescheduling framework formulated as a rolling horizon problem for the emulation of real time decision making within a dynamically changing scenario. The framework is applied to a complex multistage problem with parallel lines susceptible to disruptions as a result of process or equipment failures, or ineffective inventory management that results in material shortages. The framework is demonstrated for a simple example case which highlights the impact of disruptions on the time taken to complete orders and the associated costs. It is observed that the inclusion of disruptions can alter equipment congestion, shifting focus for future process improvements. A scenario with intermittent raw material availability is explored, with greater mean and range for a large number of simulations performed, compared to the case with constant availability. A compounding effect is observed, whereby disruptions lead to a greater likelihood of further disruptions as machine runtimes increase and tasks are repeated. The presented framework presents a strong basis from which future works could be performed in a range of scenarios and with different operating policies.

Keywords: Scheduling, Modelling, Rolling Horizon Optimization, Supply chain, Pyomo

INTRODUCTION

Process scheduling is a key component of the field of operations management, influencing decisions surrounding the timing of tasks in order to meet objectives using finite resources. Significant research efforts have been made globally in all almost all chemical and industrial engineering sectors to achieve improvements in order to minimise costs and increase efficiency. However, the practical reality of manufacturing often differs to the ideal case, and the ability to understand, anticipate, and respond to disruptions can prove to be influential in the ability to meet objectives. In this work, we investigate the role of disruptions in the scheduling of process tasks.

One popular approach for solving larger mixed integer scheduling problems is the fix-and-relax metaheuristic, which involves the fixing of variables from previous iterations and relaxing those for future periods [1]. This allows for the partitioning of large problems while keeping the current window optimisable. Prior works utilising this approach include Brahimi [2] who use the approach to handle a large problem with optional order acceptance and flexible due dates and Bouzid et al. [3] who use it to assess order acceptance under time-of-use costs and carbon taxation.

Works investigating disruptions or changing scheduling scenarios include that of Moghaddam and Saitou [4] who utilised a dynamic pegging approach to handle the predictive and reactive rescheduling of jobs upon changes to order arrivals, due dates, cancellations, and equipment failure. Hidri and Tlija [5] investigated the role of lag times (delays between tasks on a given piece of equipment) in determining the overall makespan (time taken to complete a set list of orders) of a facility. Zhao [6] investigated the handling of material in a multistage facility with uncertain job additions. The use of material handling equipment was dynamically rescheduled in response to orders, with the aim of minimising makespan.

Zheng et al. [7] investigated a dynamic problem with processing delays and demand changes. A Bayesian Network was used to understand the probability distributions for disturbances, informing ongoing decision making.

Our work presents a novel rolling horizon scheduling framework for complex multistage processes with parallel lines. The framework incorporates uncertain disruptions to process outcomes and equipment downtime, with alternative rescheduling responses based on the type of task impacted (setup, main process, or cleaning). Resource constraints and an inventory management system (with associated reorder policy) are incorporated to assess their potential for causing disruptions. An approach inspired by the fix-and-relax metaheuristic is incorporated to minimise computational requirements whilst maintaining dynamic responses that emulate real time decision making. The outcomes of the problems considered are quantified in terms of key metrics including makespan and cost.

METHODOLOGY

Problem statement

The showcased framework is targeted at the scheduling and rescheduling of a dynamically changing process. Unanticipated orders are received at set times, with disruptions in the form of process and equipment failures. Resource constraints are also considered, with an inventory management system and operating policy. The following assumptions and assertions are made to define the problem being considered.

Scheduling

- Processes are organised into stages which can perform tasks on dedicated equipment. Tasks are performed following defined recipes to complete batches
- The overall framework is split into defined time increments for the performance of additional jobs (batch addition, disruption testing, material ordering) but tasks are scheduled continuously
- Setup tasks immediately precede main process tasks which are followed by cleaning tasks
- In the presence of storage capabilities, tasks on a given stage have a defined minimum duration. Otherwise, fixed durations are defined
- Variables for tasks completed or undergoing completion are fixed in the absence of disruptions
- Potential infeasibility following disruptions is handled through the systematic unfixing of batches until feasibility is regained

Disruptions

- Disruptions occur in the form of process failures (where quality or yield deviations occur) and equipment failures (which require maintenance to be performed)
- A defined time (relative to the task start point) during material holding in storage is used to perform testing for process failures
- Failure likelihoods are known and defined as fixed probabilities
- Known distributions are used to determine the duration of equipment downtime following failure
- A defined likelihood of recovery is used to determine if repeatable tasks (e.g. purification tasks) are repeated following process failure
- Non-recovery results in material discarding and the entire batch being rescheduled. The same procedure is used should equipment failure occur during a main processing task
- Equipment failures result in equipment being blocked until maintenance is completed
- Setup, main process, and cleaning tasks are rescheduled in the event of equipment failure during a setup task
- The main process tasks are unimpacted in the event of equipment failure during a cleaning task

Costing

- The disposal of rejected material has no associated cost
- Labour costs are incurred upon the start of a main process task
- Payments for raw materials are made at the time of reorder
- Equipment repairs have no associated costs

Orders

- Orders are received at defined points and contain the order quantity, the order due date, and the desired product
- Deliveries are always completed to their fullest possible extent (based on available inventory) at the due date. Shortfalls are marked for completion at a defined later time

Inventory management

- Sufficient unallocated material must be present in order to schedule a batch

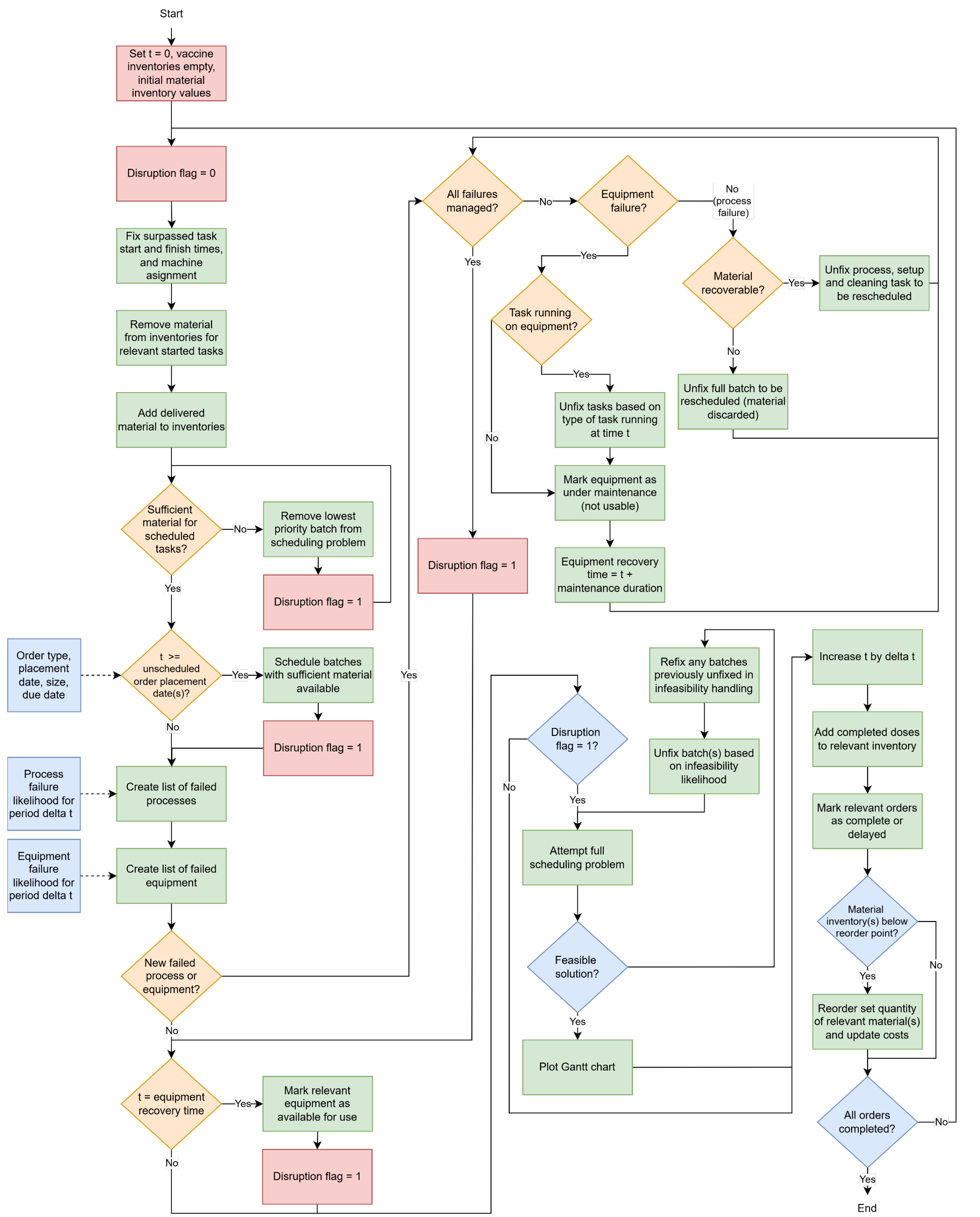

Figure 1. An overview of the presented scheduling framework used in this study

- In the case of disruption resulting in insufficient material for currently scheduled batches, the batch with the furthest due date is temporarily unscheduled

- A reorder policy is implemented based on a reorder point. Should the stored quantity of a given material reach this point, a defined quantity is reordered
- Intermittent supply refers to a case where a material is only available to reorder at defined times, unknown to the scheduler

Scheduling formulation

For brevity, the full formulation for the core scheduling problem will not be presented. A summarised version will be showcased. The key novelty of the formulation is its capacity to facilitate inputs (such as the status of a disruption) from the larger framework into the scheduling problem and allow for effective variable fixing. The objective function is the minimisation of overall makespan as shown in Equations 1. Equation 2 shows the constraint used to enforce the definition of makespan.

$$min(Makespan) \tag{1}$$

$$Makespan \geq Task\ finish\ time\ \forall\ Task\ finish\ times \tag{2}$$

The remaining constraints for the model are used to achieve the following outcomes:

1. Ensure each task is only scheduled upon a single piece of equipment
2. Ensure that the finish time of a task is equal to (for fixed duration tasks) or greater than (for variable duration tasks) the start time plus the minimum duration
3. Ensure that the start time of a successive task in a recipe for a batch is equal to the finish time of the prior task minus the duration of overlap between tasks
4. In the case of a process recovery, the prior constraint is overruled to be greater than or equal to the stated condition
5. Two tasks cannot be performed on the same piece of equipment at the same time
6. The finish times of setup tasks are equal to the start time of the associated main processing tasks, and the start time of cleaning tasks is equal to the process task finish time
7. Cleaning and setup tasks are performed on the same equipment as the main process task

Dynamic framework

An overview of the framework used to handle inventory management, order addition and completion, equipment and process disruptions, costing, and the rolling horizon model structure can be seen in Figure 1.

The framework begins with a definition of initial inventory levels followed by the main loop. The main loop first handles the fixing of variables associated with tasks completed or under completion, before managing the addition and removal of material from their associated inventories. Next, a check is performed to ensure sufficient allocated material for the currently scheduled batches, with the furthest due batch removed should current inventories be insufficient. Following this, batches from received orders that are yet to be scheduled are added to the scheduling problem, should sufficient unallocated material be available.

Process and equipment failures are determined based on their defined probabilities, creating lists of failed tasks and equipment. Should either of these occur during the current time increment, the failure handling procedure is initiated. In the event of equipment failure, currently running tasks are handled following the rules defined in the problem statement, and in all instances the equipment is marked as not usable until a later time. Should a process failure have occurred, a secondary probability is used to determine if recovery is possible, with task or full batch rescheduling as a result. Any recovered equipment is then marked as available for scheduling.

Should batch addition or removal, a process or equipment failure, or equipment recovery have occurred within the current time increment, the scheduling problem is run. Should an infeasibility occur, batches are temporarily unfixed starting with those that have been disrupted and moving onto those that are running. One batch at a time is initially unfixed, increasing once all combinations have been investigated. The first feasible solution is taken forward.

Finally, the time increment is increased, doses added to inventories, and orders completed or delayed. If inventories fall below their reorder points, those materials are reordered. This loop is repeated until all orders have been completed.

RESULTS

Demonstration of disruption impacts

In order to demonstrate the role of disruptions within the framework, a small example problem is showcased featuring the same case with and without disruptions. The example case is an eight stage process, with two pieces of parallel equipment assigned to each stage. The equipment is assigned in order, with stage 1 containing the equipment k_1 and k_2 and stage 2 containing k_3 and k_4 and so on. The stages contain a mixture of task types, with stages 1 and 1 being fixed in length, and all others containing storage and so are variable in length (above the minimum duration). Stages 3, 4, 5, and 8 represent

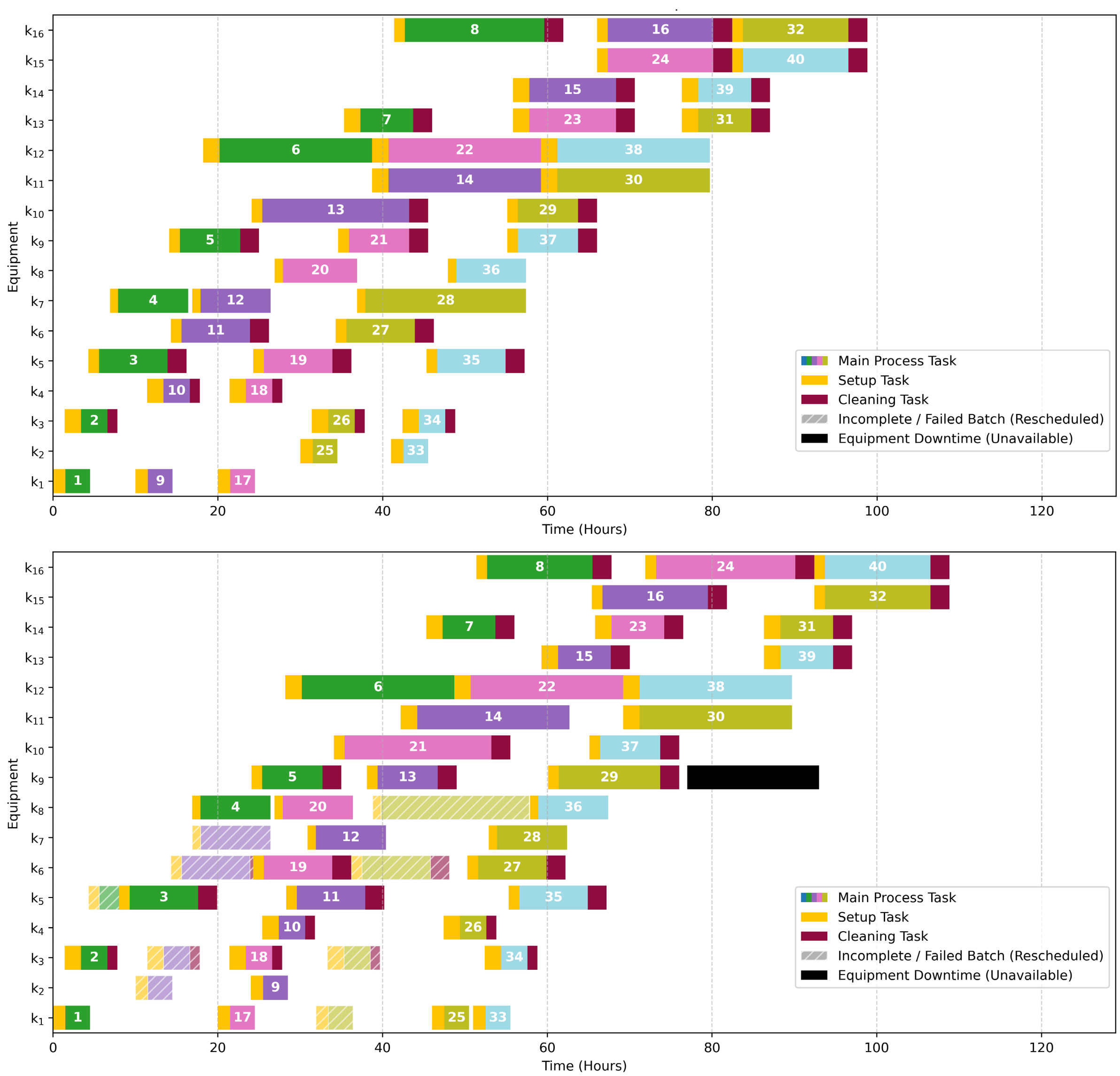

Figure 2. Gantt charts showing the scheduling of tasks for the example scenario without (above) and with (below) disruptions

purification tasks, and so have a probability of recovery following process failure. Stages 1, 4, and 6 represent processing using disposable equipment and so no dedicated cleaning is performed. The scenario shown is for the scheduling of 5 identical batches, the orders for which are received at 10 hour increments. A reorder point and reorder size of 3 batches worth of each material is used for the inventory management policy. A lead time of 10 hrs is used for the reordering of material.

Figure 2 shows the impact of disruptions on the scheduling of tasks in a singular instance of the problem. It can be seen that in the case without disruptions, the primary bottleneck is at stage 6 (equipment k_{11} and k_{12}) which sees tasks performed back-to-back. This is to be expected given that these tasks have the longest minimum duration of those within the problem. For stages 1 and 2, the use of parallel equipment is not necessary as all tasks could be performed one a singular piece of equipment without any other task being impacted. The case with disruptions demonstrates several instances of process and equipment failure. The first failure is that of task 3 at the time t=7 hrs. This task is recovered, with the remainder of the batch delayed as a result. At t=24 hrs, task 12 on equipment k_7 fails and is not recovered. This results in a full rescheduling of the batch, including the repeat of tasks 9-11. This task repetition results in a delay in the scheduling of the batch starting with task 33 at the time t=40 hrs as there is insufficient unallocated material available. At the time t=46 hrs, task 28 on equipment k_8 fails and is not recovered, resulting in a full batch reschedule in which some of the same tasks are repeated on different equipment. Upon the delivery of further

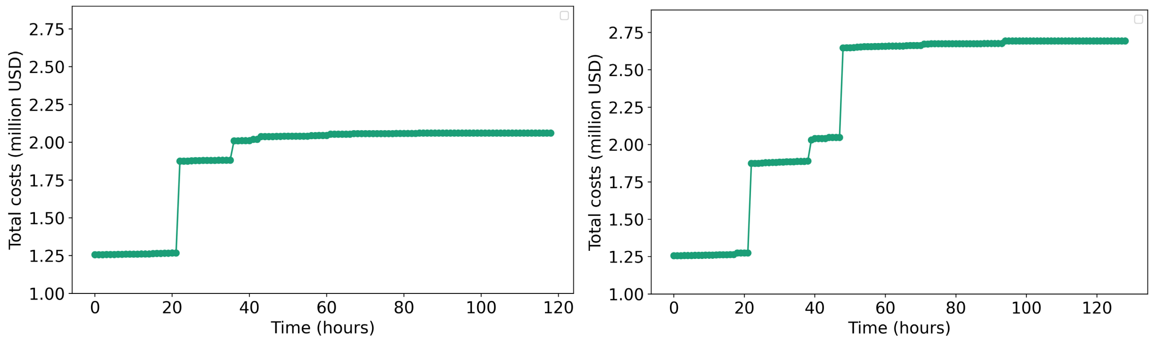

Figure 3. Cost increases over time for the example scenario without (left) and with (right) disruptions

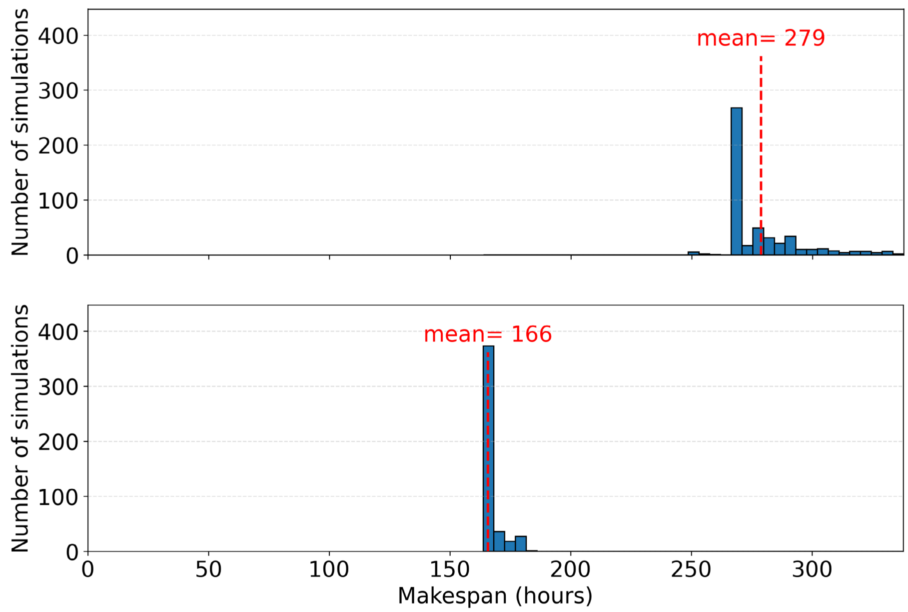

Figure 4. Makespan distributions for the case with (above) and without (below) intermittent material supply. 500 simulations were used in each case.

materials, the batch beginning with task 33 is able to be scheduled. At the time t=77 hrs, equipment k_9 fails. There is no process running and no further tasks were to be scheduled on that equipment, meaning it has no impact on overall makespan. This would not be the case in all instances of the problem.

The most noticeable impact of the incorporated disruptions is the increase in overall makespan from 98.8 hrs to 108.8 hrs. It can also be seen that the grouping of tasks changes, shifting the limiting factor from purely equipment congestion on a single stage to resource availability, changing equipment congestion, and delays themselves.

Figure 3 shows the cost in each of the same scenarios, incorporating the cost of initial raw material purchase at t=0 hrs. The case without disruptions shows that the a large increase occurs shortly after t=20 hrs. This corresponds to the purchase of materials for stage 1, which are overwhelming the highest single cost in this scenario. It can be seen that with disruptions, this reorder is repeated at t=48 hrs. This is a result of tasks being repeated, with this impact driving an overall cost increase of 30.7% as a result of disruptions.

The impact of operational policy on makespan distributions

Figure 4 shows the same case as presented previously (with disruptions) but incorporates an intermittent supply of one of the materials used in stage 6. The material is periodically available and unavailable in 8 hour increments (starting as available). To maximise the visible impact, a reorder point and quantity of 1 batches worth of material is used in both instances.

The most readily available observation is that intermittent material supply severely increases the mean makespan, representing a 68% increase in this case.

It can be seen that in both cases the distribution is right-skewed. This is partially a result of Poisson distributions used to determine equipment downtimes, but also demonstrates the compounding effect of disruptions and breaks in production due to material unavailability. The higher frequency with which these events occur, the longer the makespan and the greater the total number of tasks completed (due to repetition following rescheduling), which creates further instances for these disruptions to occur. This is also reflected in the spread of the distributions shown, with the case with intermittent supply showing a much larger range of makespans as disruptions interact with material unavailability, causing significant delays in some simulations.

CONCLUSIONS

A dynamic framework was showcased for multi-product scheduling across parallel lines with a rolling horizon approach. The scenarios explored using the framework feature several continuously changing aspects including order receival and completion, uncertain disruptions in the form of process and equipment failures, and variations in raw material availability.

The framework was applied to a small example scenario, demonstrating its capability to emulate real time decision making in response to these aspects. The inclusion of disruptions was shown to increase the makespan in the instance shown, but also results in cost increases. Equipment congestion also changed, indicating that the disruptions may alter which parts of the process would be most desirable to receive further investment or improvement. Intermittent supply of materials was found to increase both the mean and range of makespans when applied to a large number of simulations, also demonstrating a compounding impact as a result of disruptions causing further disruptions.

Further work utilising the framework could investigate different operational policies and problem structures and case studies.

ACKNOWLEDGEMENTS

This research is funded by the Department of Health and Social Care using UK International Development funding and is managed by EPSRC. The views expressed in this publication are those of the author(s) and not necessarily those of the Department of Health and Social Care.

AUTHOR IDENTIFIERS

Author ORCIDs:
Robins D: 0009-0008-5914-3977
Babaei F: 0009-0002-2179-9723
Cordiner J: 0000-0002-9282-4175
Brown SF: 0000-0001-8229-8004

REFERENCES

1. Amiri-Aref M, Doostmohammadi M. Relax-and-fix and fix-and-optimise algorithms to solve an integrated network design problem for closing a supply chain with hybrid retailers/collection centres. Computers & Operations Research 177:106981 (2025). https://doi.org/10.1016/j.cor.2025.106981
2. Brahimi N, Aouam T, Aghezzaf EH. Integrating order acceptance decisions with flexible due dates in a production planning model with load-dependent lead times. International Journal of Production Research 53:3810-3822 (2014). https://doi.org/10.1080/00207543.2014.993045
3. Bouzid M, Masmoudi O, Yalaoui A. Exact methods and heuristics for order acceptance scheduling problem under time-of-use costs and carbon emissions. Applied Sciences 11:8919 (2021). https://doi.org/10.3390/app11198919
4. Moghaddam SK, Saitou K. A novel predictive-reactive rescheduling method for products assembly lines with optimal dynamic pegging. Computers & Industrial Engineering 171:108496 (2022). https://doi.org/10.1016/j.cie.2022.108496
5. Hidri L, Tlija M. Multi-stage hybrid flow shop scheduling problem with lag, unloading, and transportation times. PeerJ Computer Science 10:e2168 (2024). https://doi.org/10.7717/peerj-cs.2168
6. Zhao C, Fu J, Xu Q. Real?time dynamic hoist scheduling for multistage material handling process under uncertainties. AIChE Journal 59:465-482 (2012). https://doi.org/10.1002/aic.13852
7. Zheng, T., Li, D., & Li, J. (2025). Bayesian dynamic scheduling of multipurpose batch processes under incomplete look-ahead information. https://doi.org/10.48550/arXiv.2512.01093