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Multi-objective Feed Reservoir Control via Optimal Pump Scheduling

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Abstract: Pumping acid mine drainage water from source to the feed reservoir that feeds the eMalahleni Water Reclamation Plant, using fixed-speed pumps, in an optimal manner takes the form of a mixed-integer quadratic programming problem. A simulation study is presented where the most optimal pumping schedule is determined using a differential evolution algorithm. The pumping schedule has to adhere to feed reservoir level constraints while minimizing composition fluctuations. The optimized pumping schedule leads to overall stabilization of the feed reservoir composition and level, which has a direct benefit to the operation of the processing plant.

Keywords: Composition control, optimization, pump scheduling, water treatment.

1. INTRODUCTION

Pump scheduling optimization has found wide application in industry (see e.g. Jowitt and Germanopoulos (1992); Ormsbee and Lansey (1994)). Standard optimization algorithms can be used when using pumps with variable-speed drives; however, many processes use fixed-speed pumps (also referred to as direct on-line pumps). The presence of fixed-speed pumps typically requires a mixed-integer quadratic programming (MIQP) problem formulation to optimize effectively.

MIQP problems can be challenging to solve in real-time. An approximation of the objective function can be solved to provide a near-optimal solution (McCormick and Powell, 2004), the MIQP problem can be re-written as a mixed-integer linear programming problem (MILP) (Wang et al., 2022), or an algorithm can be used that can directly solve the MIQP problem (Barán et al., 2005).

Solvers of MIQP formulations with non-convex objective functions can usually not guarantee global optimality. Many algorithms, however, take a global optimization approach and produce solutions that approach the global optimum in acceptable time frames.

Optimal scheduling of water pumps normally focuses on energy cost optimization and pump maintenance costs, using the number of start/stops as a proxy measure (see e.g. Ormsbee and Lansey (1994); Lansey and Awumah (1994); Mala-Jetmarova et al. (2017) for a more comprehensive review). Barán et al. (2005) added the peak power (another energy usage penalty) and reservoir level variation to the combined cost function. Mala-Jetmarova et al. (2015) found that adding water quality objectives often competes with the energy and maintenance cost objectives.

In this work, the focus is on optimizing the pumping schedule for the feed reservoir of a water treatment plant, including maintenance and water quality objectives. The eMalahelni Water Reclamation Plant (Hutton et al., 2009) converts acid mine drainage from neighbouring coal mines into potable water. The feed reservoir accepts feed from various sources with different flow rates and compositions. The reservoir level needs to be maintained, and the water quality, i.e. the specific elements of the reservoir composition, needs to be regulated.

Currently, the daily flow targets from each pump are calculated, and programmable logic controller (PLC) functionality is used to start and stop pumps such that the daily flow objectives are met. No dynamic calculations are done, and when feed pumps or downstream pumps are unavailable, the plant operator needs to intervene manually to protect the reservoir from running dry or overfilling. Both of the latter situations cause downtime, and all of these events lead to fluctuations in the composition of material in the feed reservoir.

Feed reservoir composition fluctuations lead to composition fluctuations of the processing plant feeds, leading to variability in the water treatment and, in extreme cases, to stoppages of the water treatment units.

The effective, dynamic optimization of the feed reservoir pump schedule will lead to a more consistent composition and level in the feed reservoir. This consistency translates into more stable feed into the treatment units and more consistent water treatment.

A simulation study is presented in this work where the optimal pump schedules are determined while maintaining the feed reservoir compositions under different scenarios. An effective simulation study serves as a positive proof-of-concept for implementation at the eMalahleni Water Reclamation Plant.

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2. PROCESS DESCRIPTION

The eMalahleni Water Reclamation Plant (EWRP) is a flagship water treatment plant (Grewar, 2019) that uses treatment technologies like ultrafiltration and reverse osmosis to convert acid mine drainage (AMD) into potable water. AMD is formed when sulphide minerals in mine rock or waste react with air and water to form sulphuric acid (Hutton et al., 2009).

EWRP receives AMD feed from mines in the eMalahleni area, including (Hutton et al., 2009):

- Greenside Colliery,
- Kwezela Colliery,
- Navigation Colliery, and
- South Witbank Colliery.

Feed from the Navigation Colliery originates from seven sources (see Fig. 1), that are firstly pumped to a feed reservoir by eight fixed-speed pumps. Three pumps with variable speed drives (VSD) are used to pump the AMD from the feed reservoir into the two EWRP feed ponds. From the feed ponds, the AMD goes to the two phases of the processing plant.

The seven sources of feed into the feed reservoir are:

(1) **Toe seep**: This is the coal discard leachate (Maree et al., 2004), which is an acidic stream with relatively high iron content. Toe seep is currently not routed into the feed reservoir.
(2) **Surface**: Surface water is pumped to the feed reservoir using the R51, and R52 + R54 pumps.
(3) **BH02**: This is a possible borehole feed stream that is currently not used.
(4) **BH07**: This is the feed from a borehole that allows dewatering a compartment located close to the Schoonie dam.
(5) **BH08**: This is a possible borehole feed stream that is currently not used.
(6) **BH22**: This is the feed from a borehole in a compartment located within the Navigation Colliery mining area.
(7) **BH24**: This is the feed from a borehole in a compartment located close to the Schoonie dam.

Three of the eight possible feed pumps are currently unused, leaving five possible feed sources. The critical parameter values of the five individual feed streams are shown in Table 1.

The daily target flows from each of the five pumps is determined by an optimization routine that seeks to maximize the feed from the Navigation Colliery while adhering to the following constraints:

(1) The maximum acidity limit of the phase 1 feed pond,
(2) the maximum iron content limit of the phase 2 feed pond,
(3) the maximum volumetric flow into phase 1,
(4) the maximum volumetric flow into phase 2,
(5) the respective minimum feed rates from all the other Collieries, and
(6) the respective maximum feed rates from all the other Collieries.

The optimization problem, providing the daily target flows, can be expressed as:

$$\begin{aligned} \max_{q_i} \quad & Q_{NAV} \\ \text{s.t.} \quad & \underline{q} \leq q \leq \overline{q} \\ & \underline{\alpha} \leq \alpha \leq \overline{\alpha} \\ & \underline{Q} \leq Q \leq \overline{Q} \end{aligned} \tag{1}$$

Where q_i are the individual flows with $i \in [1 \dots 5]$, α contain the compositions that are subject to constraints (the acidity and iron content), and Q contain the total flow per phase.

The solution of this optimization algorithm provides the fraction of time that each pump needs to be operational over the next 24 hours. However, this is a steady-state solution that attempts to balance the in- and out-flows and maintains the blended compositions within limits.

3. SCHEDULER DESIGN

Given the solution to the optimization problem, i.e. the fraction of time that each pump needs to run, the following problem to solve is when these pumps need to be switched on and off. There are additional considerations that need to be taken into account, which are:

(1) **Reservoir level constraints.** The reservoir level should remain within limits to prevent overflows or underflow pump cavitation. From time to time a downstream pump becomes unavailable, introducing deviations from the production plan. In these instances, the pump scheduler should adhere to the low and high limits of the reservoir level.
(2) **Reservoir composition stabilization.** Stabilizing the reservoir composition improves downstream stability and increases overall plant throughput and more consistent water treatment. Given the different compositions of the feed streams, pumps should be coordinated in an optimal fashion to minimize composition fluctuations.
(3) **Pump switching.** Each pump has minimum downtime and uptime constraints, which is the amount of time a pump must stay off after it is stopped or stay on after it was started. As an additional objective, minimizing the number of pump switches is ideal.

The reservoir level can be calculated using the mass balance, as:

$$\frac{d}{dt}V = \sum_{i=1}^{5} q_i - q_o \tag{2}$$

where q_i refers to the feed volumetric flows and q_o to the outlet volumetric flow. V is the volume of liquid in the reservoir.

The composition of the mixture in the reservoir can be calculated using the component material balance as:

$$\frac{d}{dt}(VC_{A_{j,o}}) = \sum_{i=1}^{5} q_i C_{A_{j,i}} - q_o C_{A_{j,o}} \tag{3}$$

where $C_{A_{j,o}}$ is the concentration of component j in the outlet stream and $C_{A_{j,i}}$ is the concentration of component j in the inlet stream i. The composition of the outlet

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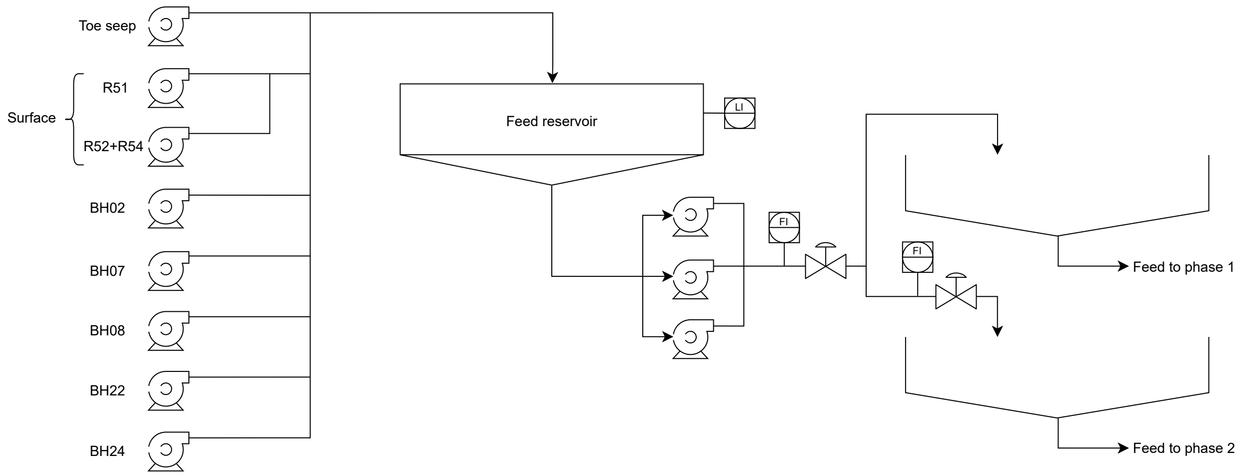

Fig. 1. Water reclamation plant feed reservoir process flow diagram.

Table 1. Key parameters of individual feed stream compositions.

Parameter	Unit	R51	R52+R54	BH07	BH22	BH24
pH	-	2.68	2.68	3.34	3.38	3.33
Alkalinity as $CaCO_3$	mg/l	5	5	5	5	5
Acidity as $CaCO_3$	mg/l	1,800	1,800	731	728	723
Dissolved Iron as Fe	mg/l	522	522	255	245	250
Total Iron as Fe	mg/l	1,600	1,600	963	634	700
Sulphate as SO_4	mg/l	3,789	3,789	2,888	2,898	2,869
Ammonia as N	mg/l	12.0	12.0	6.10	6.10	6.10
Flow while online	m^3/h	200	425	130	100	190

stream is assumed to be the same as the composition of the mixture, i.e. perfect mixing. This will not be strictly true in the reservoir, but this assumption will suffice for the scheduler design.

The optimization problem then takes the following general form:

$$\begin{aligned} \min_{\mathbf{u}} \sum_{k=1}^{N} & \|\Delta u_{k,i}\|^2_{R_1} + \|s_{l,k}\|^2_{R_2} + \|s_{\sigma_j,k}\|^2_{R_3} \\ & + \|Q_{r,i} - \sum_{k=1}^{N} q_{k,i}\|^2_{R_4} \\ & + \|l_{r,N} - \hat{l}_N\|^2_{R_5} + \|\sigma_{r_j,N} - \hat{\sigma}_{j,N}\|^2_{R_6} \\ \text{s.t. } & \underline{q} \le q_k \le \overline{q} \end{aligned} \tag{4}$$

where $\mathbf{u} : \mathbb{R} \to \mathbb{R}^{ixN}$ is the matrix of pump flows (with i pumps) over the prediction horizon of length N; $s_{l,i}$ and $s_{\sigma_j,i}$ are the respective slack variable values for the level and composition j at sample k. The slack variable value is

$$s_k = \begin{cases} y_k - y_h & ; y_k > y_h \\ y_k - y_l & ; y_k < y_l \\ 0 & ; y_l \le y_k \le y_h \end{cases}, \tag{5}$$

where y_l and y_h are respectively the variable low and high limits, and y_k is the variable value at time step k. $Q_{r,i}$ is the total flow required from pump i; $q_{k,i}$ is the flow from pump i at time step k; $l_{r,N}$ and $\sigma_{r_j,N}$ are the terminal targets for the level and compositions respectively; $\hat{l}_N$ and $\hat{\sigma}_{j,N}$ are the terminal predictions for the level and composition respectively; $\mathbf{R} = [R_1, R_2, R_3, R_4, R_5, R_6]$ is the vector of weights that are applied to terms of the objective function. These are the tuning handles that ensure the scheduler response satisfies the operational requirements.

The first three terms in (4) are stage costs, as are typically included in model predictive control (MPC) applications. The terms $\|l_{r,N} - \hat{l}_N\|$ and $\|\sigma_{r_j,N} - \hat{\sigma}_{j,N}\|$ are terminal costs that assist with placing a larger emphasis on ending the prediction horizon closer to the optimal state. Terminal costs (Köhler et al., 2019) are often added to MPC to improve stability and optimality properties (Mayne et al., 2000).

4. SIMULATION RESULTS

Various aspects of the scheduler are tested via simulation. These will be discussed in the subsections below, and are:

(1) **Optimality test.** Non-convex MIQP problems are notoriously difficult to solve. An optimal solution should be found within the execution period of the scheduler.
(2) **Level regulation during a downstream pump trip.** When a downstream pump trips and the level violates a limit, does the scheduler correct sufficiently if executed again?
(3) **Level and composition regulation when a feed pump is unavailable.** If any of the feed pumps trip or become unavailable, is the scheduler able to adequately compensate?

Euler integration is used to simulate the process over the entire prediction horizon, using the solution from (4). The volume of the reservoir, V, is 2,000 m^3. The sampling interval is set to 0.5 h (which is chosen based on the minimum down- and up-times of the pumps), and the prediction horizon is set to 10 h (which is chosen in accordance with the dynamics of the process).

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A differential evolution algorithm (Storn and Price, 1997) is used to solve for the optimal pump schedule. Differential evolution is a global optimization approach to minimize possibly nonlinear and non-differentiable functions, with comparatively faster convergence rates than many other approaches.

4.1 Optimality of the scheduler

Solvers of MIQP problems that do not have strictly convex objective functions cannot usually guarantee global optimality. The solver used here should however find an approximately optimal solution within the execution period.

To test how close the solver's approximate solution is to the true optimal, it is run for about one quarter of the sampling period. It is then run again for about the same time as the entire sampling period. The results should converge, and are generally observed to be the same. The results of the nominal simulation case are shown in Fig. 2.

The key parameter results from the nominal simulation are shown in Table 2. The fractional flows (i.e. the fraction of time that each pump should be on) required from the five sources, found by solving the steady-state optimization problem in equation (1), are:

$$f = [0.80\ 0.10\ 0.80\ 0.40\ 0.45]\,. \tag{6}$$

It is visible from Table 2 that the fractional flows in the nominal case are exactly as required. It is also clear that the pumps with the larger flows are switched less, as their switching incurs larger penalties.

4.2 Downstream pump trip compensation

In this test the scheduler is run for a couple of executions (in receding-horizon control fashion). A downstream pump then trips, such that the total flow out of the feed reservoir suddenly decreases. This leads to the level increasing, and the scheduler needs to take corrective action.

The solution found by the scheduler in this scenario is illustrated in Fig.3, with the key parameter results also in Table 2.

From the results it is clear that the scheduler has to violate the fractional flow requirements in order to prevent the level from violating constraints. This is expected as the level could not be maintained with the specified fractional flows.

4.3 Downstream pump trip when the reservoir level is high

From the previous result it may appear as though the optimizer will simply allow the level to run up when a downstream pump trips. However, the level will be allowed to run up only to the point where its contribution to the objective function becomes large enough that the optimizer must give up on e.g. the total flows required per pump.

This test is the same as the previous, where a downstream pump trips, but in this case the starting reservoir level is already high. The scheduler now needs to take further corrective action to compensate for the high level.

The solution found by the scheduler in this scenario is illustrated in Fig.4, with the key parameter results also in Table 2.

From the results it is clear that the scheduler has to violate the fractional flow requirements even further in order to prevent the level from continuing to increase. This is expected as the level could not be maintained with the required fractional flows.

4.4 Feed pump unavailability compensation

If any of the feed pumps become unavailable, the scheduler should still find the optimal solution for all other pumps such that the level and composition are maintained.

In this scenario it is assumed that the R51 pump is down for maintenance, and that it is unavailable to the scheduler. This is easily set up in equation (4) by specifying $\overline{f} = 0$ for R51. The results of this scenario are illustrated in Fig.5, with the key parameter results also in Table 2.

In this scenario it is clear from the results that the flow of R51 remains at 0 throughout, as per definition of the scenario. It is also visible that the fractional flow of pump R52+R54 are slightly higher than what was specified by the solution of (1), which sufficiently compensates for the unavailability of R51.

4.5 Simulation results summary

The key parameter results of the four scenarios simulated in this section are shown in Table 2.

The scheduler is able to find approximately optimal solutions within the execution period for the different scenarios that were simulated. In the nominal case it is able to match the fractional flow requirements while minimizing switching and regulating the composition.

When upstream or downstream pumps are unavailable, the scheduler is able to give up on the fractional flow requirements to protect the level and composition.

5. CONCLUSION

The optimal scheduling of fixed-speed reservoir feed pumps was addressed in this paper. Normally, pump scheduling optimization is concerned with energy cost optimization with tiered or time-of-use based pricing. However, in this work a multi-objective cost function is formulated by means of which the scheduler attempts to maintain the reservoir level while stabilizing the reservoir composition.

The scheduler is simulated in different scenarios, and is able to meet the objectives even when upstream or downstream pumps are unavailable. This successful simulation study serves as a positive proof-of-concept for implementation at the eMalahleni Water Reclamation Plant.

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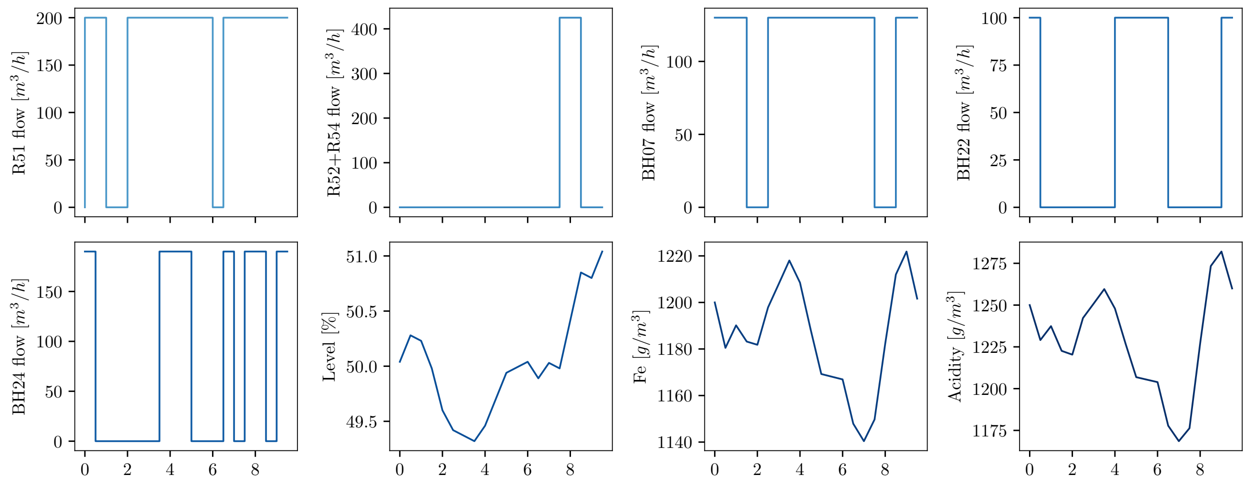

Fig. 2. Nominal simulation case results. Variables are displayed as functions of time in hours.

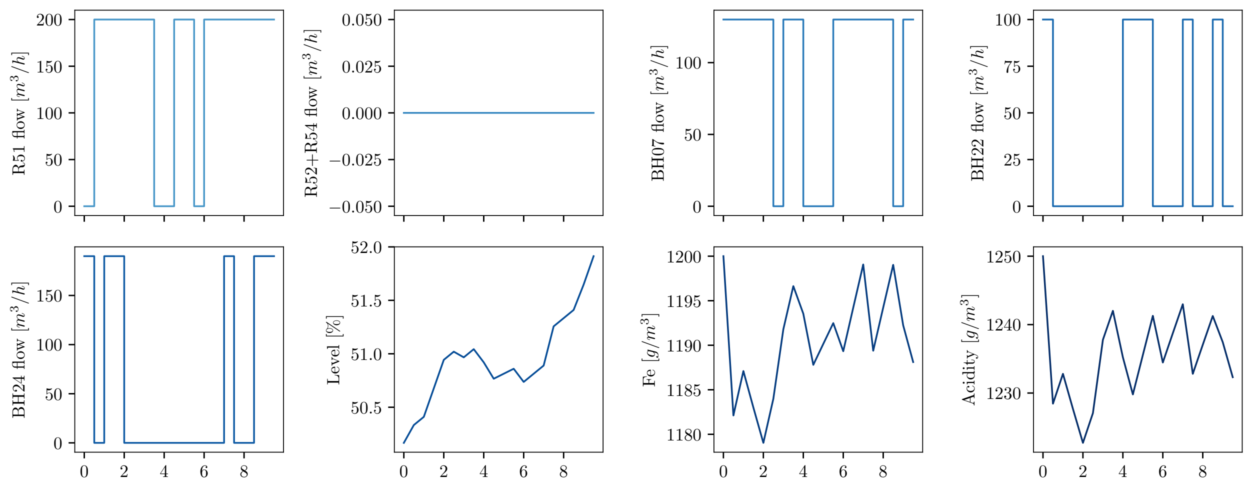

Fig. 3. Scheduler results when a downstream pump trips. Variables are displayed as functions of time in hours.

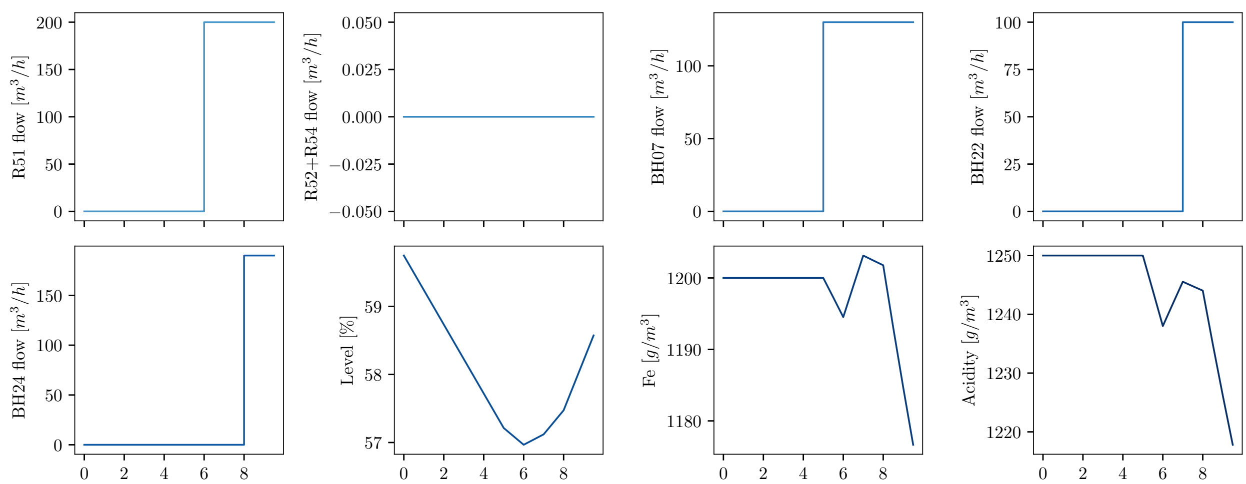

Fig. 4. Scheduler results when a downstream pump trips and the reservoir level is already high. Variables are displayed as functions of time in hours.

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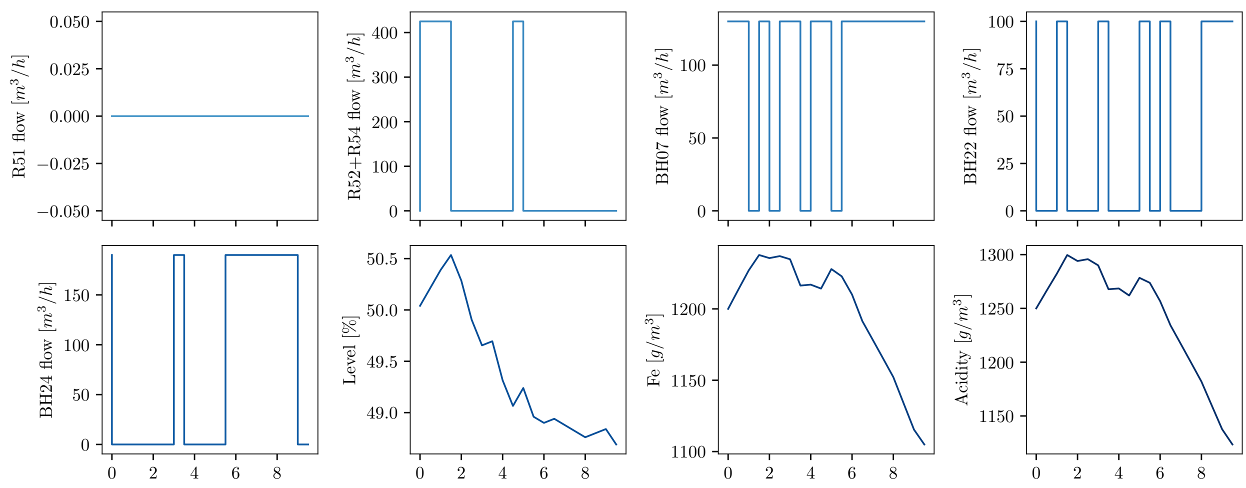

Fig. 5. Scheduler results when the feed pump R51 is unavailable. Variables are displayed as functions of time in hours.

Table 2. Key parameters from simulation result cases.

Parameter	Nominal case	Downstream trip	Downstream trip with high level	Feed pump (R51) unavailable
Frac. flow 1	0.80	0.75	0.35	0.00
Frac. flow 2	0.10	0.00	0.00	0.20
Frac. flow 3	0.80	0.75	0.45	0.80
Frac. flow 4	0.40	0.35	0.25	0.40
Frac. flow 5	0.45	0.35	0.15	0.45
# switches 1	5	5	1	0
# switches 2	2	0	0	4
# switches 3	4	6	1	8
# switches 4	4	7	1	10
# switches 5	8	6	1	5

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