# A Simulation-based Local Search Algorithm for Real-time Mitigation of Power Peaks in Railway Networks

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## 1 INTRODUCTION

Power peaks are an undesirable phenomenon occurring in railway networks when multiple electric trains require a large amount of power simultaneously, putting pressure on the power grids (Scheepmaker *et al.*, 2017). Furthermore, with increased traffic supply in recent years, the chances of having power peaks above certain levels increase, while at the same time, upgrading or over-dimensioning energy supply systems is very costly. The mitigation of power peaks in railway networks becomes hence a relevant issue for train operating companies due to its potential to reduce electricity consumption and operational costs without incurring the substantial costs associated with infrastructure enhancements (Albrecht, 2014, Trivella & Corman, 2023). Simultaneous train accelerations can cause significant power peaks, whereas energy from regenerative braking during decelerations could be used by other trains (Wang *et al.*, 2022).

Related research explored the mitigation of power peaks by means of timetable adjustment (Bärmann *et al.*, 2017, Wang *et al.*, 2022), and acknowledges the fact that the benefits of energy-efficient train timetabling can be lost easily in delay scenarios. By contrast, other studies have focused on real-time control and scheduling (Albrecht, 2004). Common strategies for mitigating power peaks, such as adjusting departure times and synchronizing power consumption, must be balanced with real-time scheduling to prevent traffic conflicts, especially on busy or single-track lines. In this work, we propose a novel simulation-based local search approach for the mitigation of power peaks in railway networks and rescheduling in real-time using two types of control measures: departure time shift and traction power limitation.

## 2 METHODOLOGY

We address the problem of mitigating power peaks and rescheduling in real-time (RPMR). This is done by predicting power peaks to occur within a look-ahead time horizon and implementing appropriate train control measures for specific trains at specific track sections to mitigate those, while having full knowledge of the state of the train traffic at any point in time. We define a power peak as the event where the power consumption of all trains combined in a region of space in a certain time interval exceeds a certain limit value. Therefore, mitigation of a power peak involves shaving the power peak under the limit value. Possible control measures to achieve so include departure time shift and traction power limitation, and we model them as discrete choice sets to ensure their applicability in real-life settings. The RPMR problem takes as inputs: (1) a detailed model of the railway infrastructure, (2) a given feasible timetable and (3) precomputed train trajectories and associated power consumption profiles for different maximum power levels, and (4) predefined choice sets for train control measures. The problem outputs the chosen train control measures and hence an adjusted operations plan.

The problem's search space grows exponentially with the size of the choice sets, the number of trains controlled, and the number of power peaks in the planning horizon, resulting in potentially many near-optimal solutions. In the context of a real-time application, we aim to find a solution in a short time (seconds), not necessarily optimal, such that all the power peaks in the planning horizon are mitigated. Therefore, we propose a simulation-based local search algorithm for the RPMR problem. The framework combines a detailed train traffic simulator with a local search strategy to efficiently explore and rank combinations of control measures, balancing the mitigation of power peaks and adherence to the timetables. We describe first the simulation tool (subsection 2.1) and second the simulation-based local search approach together with the benchmark used (subsection 2.2).

## 2.1 Simulation of Railway Traffic

We adopt a synchronous discrete-event simulation approach for real-time traffic management, which allows us to accurately model train traffic with low computational cost (effectively bypassing complex *NP*-hard mathematical formulations), suitable for real-time fast applications. The simulator manages the dispatching decisions (namely, retiming of events) to ensure the feasibility of train traffic and models the signalling system assuming a 3-aspect 2-block system to ensure safe train movements (e.g. headways and track reserves). Train trajectories are precomputed with a 1-second resolution and assume maximum acceleration (within the predefined power level available) and braking rate, use of regenerative braking and no coasting. It takes as inputs the detailed infrastructure, the timetable and the precomputed trajectories and power profiles. The main loop of the simulation algorithm manages the event triggers, generated based on the scheduled arrival and departure time of trains, and dispatches each train if the required sections are not blocked by other trains. The main outputs of the simulation, based on the actual trajectory realizations of trains, are (1) the power-time diagram, which shows the power consumption over time, (2) the time-distance diagram, and (3) the resulting arrival and departure delays.

## 2.2 Simulation-based Local Search Approach

We aim to minimize an objective function that balances total delay, number of power peaks, and traffic conflicts, weighted by $w_1$, $w_2$ and $w_3$ (i.e. penalties), respectively (Equation 1). The total delay is measured as the difference between scheduled and actual arrival time at each station and a conflict takes place when a train has to wait before entering a section due to occupied infrastructure. We accept new solutions if they lead to a lower value of this objective function.

$$f(\mathcal{S}) = w_1 \cdot TotalDelay + w_2 \cdot PowerPeaks + w_3 \cdot TrafficConflicts \tag{1}$$

We present the pseudocode of the approach proposed in Algorithm 1. An initial solution $\mathcal{S}_0$ for the local search algorithm is obtained by running the simulation once with trains adhering to the timetable and independently of possible power peaks incurred. If the initial solution has power peaks above a certain value, a while loop is initialized, which runs for a maximum number of iterations. A neighbour solution $N(\mathcal{S})$ is generated. This is done by ranking all the combinations of control measures choice sets for the top trains contributing to the identified power peaks. These prioritize applying power limitations before resorting to time shifts for a practical preference to minimize delays. The generation of a neighbour walks stepwise on this ranking for each power peak. The objective of the neighbour solution $f(N)$ is compared with that of the current solution $f(\mathcal{S})$. If $f(N)$ is lower, then the current solution $\mathcal{S}$ is updated as well as its objective $f(\mathcal{S})$. Otherwise, the while loop continues generating more neighbour solutions within the ranking of control measures combinations. If the solution is feasible, i.e., no power peaks are left, the algorithm terminates.

**Algorithm 1** Simulation-based Local Search Algorithm for the RPMR Problem

```
Initialization: Initialize timetable, control measures choice sets and all parameters
Get initial solution S_0 and objective function value f(S_0)
Rank combinations of control measures choice sets for top trains contributing to each peak
while num power peaks > 0 and not converged within maximum number of iterations do
    Generate a neighbor solution N(S) by adjusting train control measures and evaluate f(N)
    if f(N) < f(S) then
        S ← N(S) and update f(S)
    end if
end while
return feasible solution S
```

We use an Exhaustive Enumeration with pruning (PEE) approach with a modified Breadth-first search to benchmark the local search approach. This algorithm explores the planning horizon chronologically, evaluating train control combination decisions for each power peak. Only combinations that effectively mitigate the next peak will be further explored (i.e. deeper in the search space). The benchmark allows us to find an optimal solution within the bounds of the predefined choice sets.

# 3 RESULTS

We demonstrate the performance of the approach developed in the 40-kilometer-long line between Biasca and Locarno from the Swiss Federal Railways. The line is fitted with a double-track in 80% of its length, with the rest featuring a single track. We use an input published timetable from a basic hour pattern from 2022 with 28 trains (mixed passenger traffic with different stop patterns) over a duration of two hours, during which the trains are gradually added to the line, assuming no external disturbances in the planned operations. We use the choice sets for departure time shifts $S = \{0, 30, 60\}$ (seconds) and power limitation levels $L = \{50, 100\}$ (%), up to two trains controlled per peak, and weights $w_1 = 1$ and $w_2 = w_3 = 100$.

Table 1 – *Overview of Performance Results*

| | Runtime (s) | Iterations | # Shifted trains | Average shift per train (s) | # Trains with limited power | Total additional arrival delay (s) |
|---|---|---|---|---|---|---|
| PEE | 600[a] | 3,234[b] | 2 | 60 | 4 | +26 |
| SLS | 0.77 | 3 | 6 | 30 | 12 | +84 |

[a] Timeout in 600 s, but feasible solutions found. First valid solution found in 129.6 s.
[b] Number of explored solutions.

For illustrative purposes, we use the case with a maximum power limit of 14 MW, which with the planned timetable results in 6 power peaks. The overview of results is reported in Table 1 for the simulation-based local search approach (SLS) and the benchmark (PEE), showing the total runtime, number of iterations of the algorithms, number of shifted trains, average time shift per shifted train, number of trains with limited power and total additional arrival delay, measured with respect to the initial solution $\mathcal{S}_0$ (i.e. ignoring power peaks and adhering to the timetable) over all stops. The PEE returns the solution with the best objective. The objective is equal to the total arrival delay in seconds since in the feasible solutions there are no power peaks left nor traffic conflicts (Equation 1). Furthermore, the additional arrival delay resulting from the control measures is very small in both approaches, and thus it has no negative effect on passenger satisfaction. The larger delay in SLS results from the longer trajectories of certain trains due to power limitation in certain sections. Finally, Figure 1 presents the power-time diagram from the initial solution (left) and optimized solution (right) in the time interval of 40 to 70 minutes (2 power peaks), where the blue line represents the total consumption at each second.

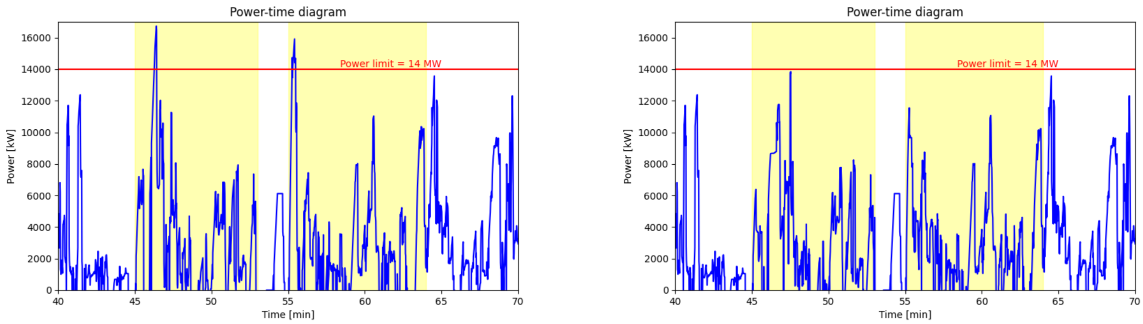


Figure 1 – *Power-time diagram from initial solution* $\mathcal{S}_0$ *(left) and optimized solution (right) with power limit = 14 MW in the time interval [40, 70] minutes. The highlighted areas represent those time intervals where effects from control measures in the trajectories have been propagated.*

# 4 DISCUSSION

We have shown the potential of the simulation-based local search approach developed to address the problem of integrating the mitigation of power peaks with traffic rescheduling in real-time with a very fast solving time and delivering nearly optimal solutions.

Our work focuses on the fluctuations in power consumption rather than the total amount of energy consumed. Nonetheless, the energy bill usually depends on both (Albrecht, 2004). Therefore, the potential of our approach to mitigate power peaks in real-time with small adjustments in operations shows the potential to reduce energy costs for the infrastructure manager in the context of increased pressure for energy efficiency, as well as contributing to a more resilient power grid. Lastly, applying our approach in practice is challenging since railway operations are subject to many uncertainties affecting train trajectories and running times, and it would require dynamic driver support systems or automatic train operation.

# References

Albrecht, Thomas. 2004. Reducing power peaks and energy consumption in rail transit systems by simultaneous train running time control. *Advances in Transport*, **15**, 885–894.

Albrecht, Thomas. 2014. Energy-Efficient Railway Operation. *Chap. 5, pages 91–116 of:* Hansen, I.A., & Pachl, J. (eds), *Railway Timetabling & Operations*. Hamburg: DVV Media Group GbmH | Eurailpress.

Bärmann, Andreas, Martin, Alexander, & Schneider, Oskar. 2017. A comparison of performance metrics for balancing the power consumption of trains in a railway network by slight timetable adaptation. *Public Transport*, **9**, 95–113.

Scheepmaker, Gerben, Goverde, Rob M.P., & Kroon, Leo G. 2017. Review of energy-efficient train control and timetabling. *European Journal of Operational Research*, **257**(2), 355–376.

Trivella, Alessio, & Corman, Francesco. 2023. Modeling system dynamics of interacting cruising trains to reduce the impact of power peaks. *Expert Systems with Applications*, **230**, 120650.

Wang, Pengling, Bešinović, Nikola, Goverde, Rob M.P., & Corman, Francesco. 2022. Improving the Utilization of Regenerative Energy and Shaving Power Peaks by Railway Timetable Adjustment. *IEEE Transactions on Intelligent Transportation Systems*, **23**(9), 15742–15754.