# Generation and Optimization of Train Timetables Using Coevolution

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Train timetabling is a process of assigning suitable arrival and departure times to trains at the stations they visit and at key track junctions. It is desirable that the timetable focusses on passenger preferences and is operationally viable and profitable for the Train Operating Companies (TOCs). Many hard and soft constraints need to be considered relating to the track capacities, set of trains to be run on the network, platform assignments at stations and passenger convenience. In the UK, train timetabling is mainly the responsibility of a single rail infrastructure operator - Network Rail. The UK rail network has a structure that is complex to integrate, which makes it difficult to achieve regularised train timetables that are common in many European countries. With a large number of independent TOCs bidding for slots to operate over limited capacities, the need for an efficient and intelligent computer-aided tool is obvious. This work proposes a Cooperative Coevolutionary Train Timetabling (CCTT) algorithm concerned with the automatic generation of planning timetables, which still demands a high degree of accuracy and optimization for them to be useful.

Determining the departure times of the train trips at their origins is the most critical step in the timetabling process. Timings of the train trips en route can be computed from the departure times. Pathing is the time added to or removed from a train's journey from one station to another. The amount of duration a train stops at the station is the dwell-time. Along with the departure and arrival times at every station, a train's journey also needs to determine track and platform/siding utilisation from origin to destination.

The idea of parallel evolution of problem subcomponents that interact in useful ways to optimize complex higher level structures was introduced by [3]. The advantages of such decomposition are independent representation and evolution of interacting subcomponents that facilitate an efficient concentrated exploration of the search space. The decision variables of the train timetabling problem are substructured into coevolving subpopulations - the departure times ($P_d$), scheduled runtime and dwell-time patterns ($P_p$) and capacity usage ($P_c$). Departure time of the trains being key to timetable generation, is evolved by Evolution Strategy [2]. An adaptive mutation strategy is used to control the trains' departure time evolution with a higher probability for finer mutations. Scheduled runtime of a train is the normal travel time of a train combined with variations to the travel time during a train's journey. Switching between high and low scheduled runtimes and dwell-times for trains is performed through a binary representation. Hence, $P_p$ is evolved through a Genetic Algorithm [1]. The

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rail network being considered assumes a single track system (one track in each direction) between stations with two platforms available at each station. This network set-up facilitates platform allocation and helps identify constraint violations. With either of the two platforms to be utilised by a train at each station, $P_c$ evolves using a simple GA framework using binary chromosomes. The individual being evaluated and the representatives from collaborating populations generate a complete timetable. A greedy collaborator selection method [4] is undertaken. The individual being evaluated is assigned a fitness proportional to that of the complete timetable. The fitness function identifies and penalizes hard and soft constraint violations at the conflict points.

We run the algorithm with different random seeds for 5 times and the results achieved after 1000 iterations by CCTT are promising (shown in table 1). Considering the use of the same cost function, the quality of results i.e. the exploration of search space is better than those from a two-phase Simulated Annealing (SA) algorithm similar to the Planning Timetable Generator (PTG), which is a sophisticated train timetable planning tool developed by AEA Technology, Rail.

**Table 1.** Test Results from an average of 5 runs of the algorithm

| | SA | | | CCTT | | |
|---|---|---|---|---|---|---|
| Test Case | Best Fitness | Avg. Fitness | Time (sec) | Best Fitness | Avg. Fitness | Time (sec) |
| T-50 | 4064 | 4368 | 3.84 | 3395 | 3857 | 4.79 |
| T-80 | 6064 | 6965 | 5.73 | 5575 | 6276 | 7.13 |

This research is on-going. The next phase of research will further refine the collaborative coevolution approach with further experiments and testing using real-world data sets.

## References

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