Heuristic to propose Few Distinct Solutions to the Additional Train Scheduling Problem

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Abstract

As railway passenger demand rises and as timetables get tighter, the need for reliable additional train scheduling increases. While academic research has made progress in automating train scheduling, these advances often struggle to transfer directly into practice. One important issue is the objective function: studies typically simplify the problem to one to three objectives, but real-world deployments require many more to produce practically implementable solutions. Equally important is that many different factors influence whether a schedule is of high quality — not just whether the computed timetable is conflict-free. Understanding the trade-offs between these multiple objectives and how they shape the set of feasible solutions remains difficult. This work therefore aims to provide a small, carefully chosen set of distinct solutions that perform well across a range of relevant objectives. A framework using simulation, clustering, and a set covering problem is proposed to find solution clusters and their representative weight vectors. Then, a heuristic is proposed to calculate these few distinct solutions on new instances quickly. Fourteen corridors of the Swiss national railways are used as a test case. Two thousand instances per corridor are generated randomly with different weights of five objectives. Clustering allows to find between 1 and 9 solution clusters for all corridors. Cross-validation shows that the heuristic performs on average with 75% cluster coverage. The generalization of the approach over many railway corridors is thus promising.

Keywords

Railways; Additional train; Timetabling; Heuristic; Optimization; Multi-objective; Clustering; Set covering problem; Cross-validation

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1 Introduction

With increasing interest in rail transportation, the capacity of rail networks is coming to its boundary. Aside from long-term and expensive infrastructure developments, capacity can be increased by optimizing train timetables. Consequently, a research stream emerged to automate and optimize timetabling problems. One sub-task of the timetabling process is the additional train scheduling, which we will focus on in this work.

Despite the advances of academia in timetabling optimization, limitations in regards to applicability to practice persist. One example is the simplification of the objective function. Research works considering more than four objectives and exploring the solution space are lacking. However, more objectives are needed to depict real-world conditions. A further challenge for practitioners is understanding the behavior of multiple objectives and their influence on the solution space.

The contribution of this work is to deliver a limited number of distinct solutions that are satisfactory w.r.t. various objectives. To do so, a framework using simulation, clustering, and a set covering problem is proposed to find solution clusters and their representative weight vectors. Additionally, a heuristic based on these representative weight vectors allows to calculate quickly distinct solutions on new instances. Finally, cross-validation is used to evaluate the heuristic.

The approach is applied on fourteen corridors of the Swiss national railways (SBB). Two thousand instances per corridor are generated by randomly selecting different weights of five objectives. Each instance is solved using the solver of the SBB additional train scheduling tool, which is already used in production at SBB since 2023. Clustering results allows to find until 9 solution clusters per corridor. Cross-validation results show that the heuristic performs with an average of 75% cluster coverage. This work thus shows the potential for the generalization of the approach over different railway corridors.

The paper is structured as follows. Section 2 reviews the literature of additional train scheduling and its multi-objective optimization applications. Section 3 presents the problem that this work aims to solve. Section 4 introduces the framework, heuristic and its validation as well as the clustering and the set covering problem. Section 5 gives details on the experiment design and the SBB test case. The results are presented in Section 6. Section 7 discusses the approach, and Section 8 concludes.

2 Literature Review

The additional train scheduling problem consists of scheduling one train path in an existing timetable. The existing timetable already contains several train paths, so-called context trains. A solution to the problem is the path of the additional train, avoiding conflicts with context trains. The following multi-objective studies of the problem are notable. Flier *et al.* (2009) studies predicted delays of additional trains and travel time on a Pareto front. Burdett and Kozan (2009) optimizes the time window violations and the schedule quality. Gao *et al.* (2018) minimizes the total travel time of the additional trains and the adjustment on the existing trains. Chow and Pavlides (2018) studies the effect of inserting additional trains on the four objectives of crowdedness, journey time, punctuality, and waiting time and pursues independently a Pareto analysis. Tan *et al.* (2020) minimizes both the total adjustments for initial trains and the number of required train sets. Zhao *et al.* (2024) conducts a sensitivity analysis on the weights of the three objectives of unserved demand, delays of freight trains, and disruptions to planned passenger trains. Feng *et al.* (2024) minimizes the operating cost of providing train capacities for passengers, the cost for the utilization of vehicles and the cost of adding trains from the capacity pool. However, no study considers more than four objectives in additional train scheduling.

3 Problem Definition

To close the gap of planning pragmatically with multiple objectives, the goal of this work is to propose distinct and few solutions. The first question that arises is which solutions exist. This can be answered by varying the objective weights in the objective function. The consequent question is whether there are indeed only a few distinct solutions. In other words, we need to check whether the resulting solutions are redundant. For this sake, we need to define under which conditions solutions are considered to belong to the same group of distinct solutions. Clustering approaches can help to group solutions together and to count the number of distinct solutions. Finally, one would like to get these few and distinct solutions quickly if they exist. This can be achieved through a heuristic that doesn't need to explore the whole solution space. Considering that representative solutions can be drawn for each group of distinct solutions, the hypothesis of this research is that the corresponding representative weights can find distinct solutions over different railway corridors. Hence, this paper aims to find these representative weights as a basis for the heuristic. Generalizability should be validated over many railway corridors, to verify the hypothesis. This can be achieved through cross-validation.

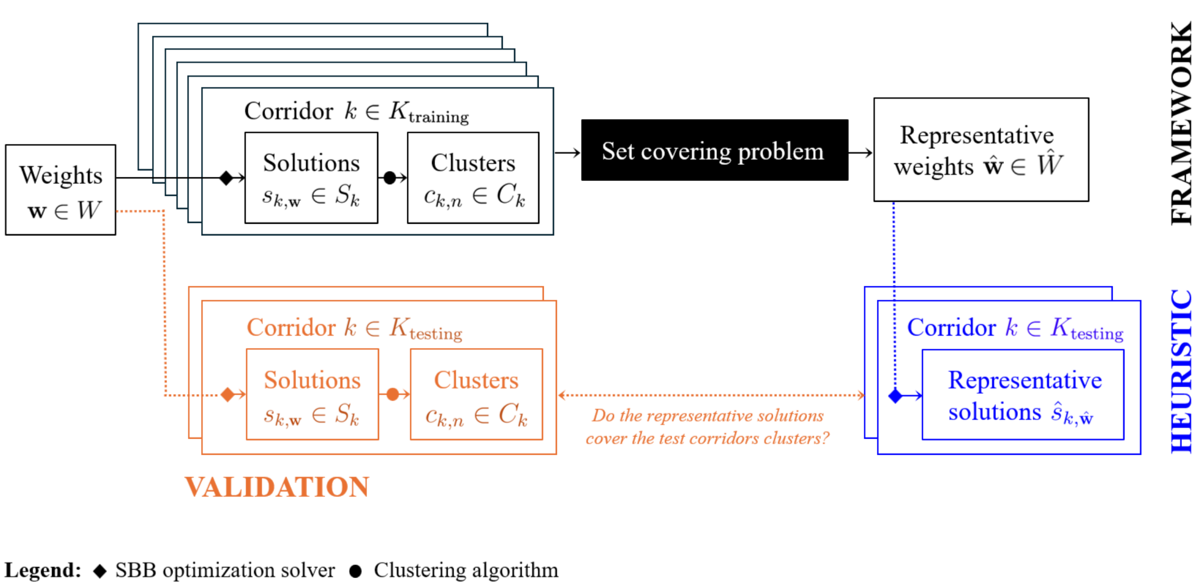
4 Methodology

Before introducing the framework and the heuristic in more detail, we need to define:

- **Corridor** $k \in K$: timetable of a railway line with additional train requirements.
- **Weight vector** $\mathbf{w} \in W$: weights of the objectives for an instance to optimize.
- **Solution** $s_{k,\mathbf{w}} \in S_k$: additional train path solution of the instance $(k,\mathbf{w})$.
- **Cluster** $c_{k,n} \in C_k$: cluster n of similar solutions of corridor k, where $c_{k,n} \subseteq S_k$.
- **Representative weight vector** $\hat{\mathbf{w}} \in \hat{W} \subset W$ **and their solutions** $\hat{s}_{k,\hat{\mathbf{w}}} \in S_k$: vectors covering clusters of several corridors and their corridor-specific solutions.

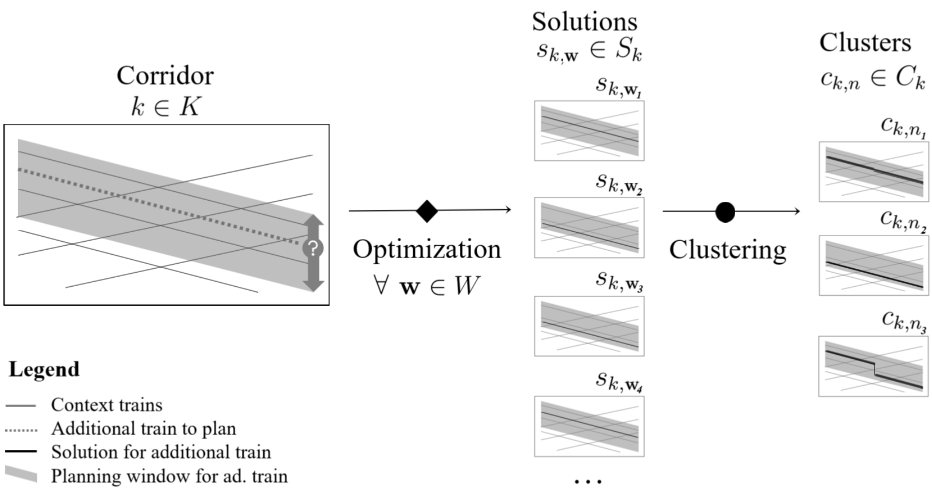
Framework, heuristic, validation. The goal is to find from all weights representative ones to provide few distinct solutions (Figure 1). To do so, the corridors $k \in K$ are split into a training set K_{training} for the framework and a testing set K_{testing} for the heuristic validation. In the framework pipeline, a set of weight vectors $\mathbf{w} \in W$ is used to weight the objective function for each corridor's additional train problem in different manners. Thus, for each corridor $k \in K_{\text{training}}$, we generate additional train path solutions $s_{k,\mathbf{w}} \in S_k$ thanks to the SBB solver. These solutions are grouped into clusters $c_{k,n} \in C_k$. Then, all clusters of all corridors are given as inputs to the set covering problem and yield a set of representative weight vectors $\hat{W} << W$. The aim is to cover with the minimal amount of weight vectors $\hat{\mathbf{w}} \in \hat{W}$ clusters of all corridors in K_{training}. In the heuristic pipeline, $\hat{W}$ allows to calculate directly representative solutions $\hat{s}_{k,\hat{\mathbf{w}}} \in S_k$. Finally, we validate these representative solutions on K_{testing}, by looking at the amount of clusters covered.

Figure 1: Framework (in black), heuristic (in blue) and validation (in orange)



Clustering. Figure 2 shows how a corridor optimized with different weights yield different solutions, which are in turn clustered. The time values of the solution path are used to build clusters. Clusters are groups of similar solutions of a same corridor. We define similarity as both the closeness of solutions of the same cluster and the distance of solutions from other clusters. Closeness can be measured as the amplitude between solutions in one cluster and distance as the gap from one cluster to another. We define thresholds for closeness and distance. To find the number of clusters per corridor, we first apply the k-mean elbow method on the time values of each additional train path solution. Then, we increment the number of clusters until the closeness threshold is met. Finally, we merge all clusters where the distance threshold is not met.

Figure 2: Clustering: corridor $k \in K$, solutions $s_{k,\mathbf{w}} \in S_k$, and clusters $c_{k,n} \in C_k$



Set covering problem (SCP). The objective is to select as few weight vectors as possible such that all clusters of the training corridors are covered. Each weight vector can cover multiple clusters of different corridors. We define the decision variable $x_{\mathbf{w}} \in \{0, 1\}\ \forall\ \mathbf{w} \in W$, which is equal to 1 if $\mathbf{w}$ is selected. We define $W_{k,n}$ representing the weight vectors of the solutions belonging to cluster $c_{k,n}$. Below is the formulation of the corresponding set covering problem. The result represents the representative weight vectors $\hat{\mathbf{w}} \in \hat{W}$.

$$\min \quad \sum_{\mathbf{w} \in W} x_{\mathbf{w}} \tag{1}$$

$$\text{s.t.} \quad \sum_{\mathbf{w} \in W_{k,n}} x_{\mathbf{w}} \geq 1 \quad \forall c_{k,n} \in C_k; \forall k \in K_{\text{training}} \tag{2}$$

5 Experiments

SBB additional train scheduling model. To run the experiments, we use the code of the microscopic timetabling tool developed by SBB. The tool is used daily by its planners to schedule additional trains. The tool's algorithm is described in Brugger *et al.* (2025). The optimization problem at the core of the tool is formulated as a mixed-integer program (MILP). The problem is solved with the commercial solver Gurobi.

Corridors. We consider 7 railway lines in both directions, yielding 14 corridors. Their timetables are real operational days. Table 1 shows the number of context trains, possible stops, and single tracks. Appendix A gives an overview of the topologies of the corridors.

Objectives. We consider the five following objectives: runtime, path, stop, supplement, and separation. They are formulated as a weighted sum in the objective function. Table 2 presents their original weights and describes their case of optimality. For more details on their meaning, we refer to Brugger *et al.* (2025). The objective function also contains the soft constraints conflict and earliness.

Table 1: Corridors information: number of context train, possible stops, and single tracks

Corridor name	Number of context trains	Number of possible stops	Number of single tracks
TW-SA	155	28	1
SA-TW	152	28	1
PAL-FLM	122	22	0
FLM-PAL	121	22	0
EBR-ZF	80	18	0
ZF-EBR	81	18	0
VV-VI	75	40	0
VI-VV	75	40	0
PR-GD	170	46	0
GD-PR	172	46	0
OWT-RH	146	19	0
RH-OWT	142	19	0
WGR-GSS	104	21	0
GSS-WGR	102	21	0

Source: SBB solver

Weight vectors. We generate randomly 2000 weight vectors. To do so, we multiply the original weights (see Table 2) by factors in the range [0.01,100] centered in 1. We ensure that the 5-dimensional space is evenly covered using Latin hypercubes.

Table 2: Objective, original weights, and case of optimality

Objective	Weight	Case of optimality
Separation	1	30 sec. above minimum mandatory release time added
Path	2	best route quality score of the selected path
Runtime	0.1	minimal duration between departure and arrival stations
Supplement	1.1	each train's driving time 2% above minimum runtime
Stops	0.01	no unplanned stops

Source: SBB solver

6 Results

Clustering yields few distinct solutions. Table 3 presents the results of the clustering of the instances built with the weights and corridors introduced in Section 5. For the closeness threshold, we consider an amplitude mean of 2 minutes. On the other hand,

Table 3: Clustering results: number of clusters and instances, worst closeness and distance

Corridor name	Number of clusters	Min. instances per cluster	Worst cluster closeness (sec)	Worst clusters distance (sec)
TW-SA	3	117	139.33	45.07
SA-TW	2	710	97.28	118.96
PAL-FLM	1	-	58.57	–
FLM-PAL	2	69	47.04	1762.19
EBR-ZF	2	187	41.46	1650.97
ZF-EBR	1	-	73.85	–
VV-VI	1	-	156.76	–
VI-VV	4	160	392.95	32.16
PR-GD	3	219	157.57	219.16
GD-PR	2	294	149.65	1516.78
OWT-RH	8	3	166.15	30.68
RH-OWT	1	-	67.16	–
WGR-GSS	3	9	73.47	113.17
GSS-WGR	9	11	47.59	44.71

for the distance threshold, we split the time values into 10 equal sub-sets and merge clusters where all sub-set distance means with other clusters are below the threshold of 2 minutes. This yiels a variety of cluster numbers among corridors. GSS-WGR and OWT-RH have the highest number with respectively 9 and 8 clusters. The corridors PAL-FLM, ZF-EBR, VV-VI, and RH-OWT have a single cluster. These single-cluster corridors are excluded for the next step, as they would create useless constraints to the set covering problem. Hence, 10 of the initial 14 corridors remain. Appendix B gives a visual preview of these solution clusters. The clustering results confirm that few and distinct solutions exist. The next step is to find those more quickly thanks to the heuristic.

Cross-validation to evaluate the heuristic. To evaluate the validity of the heuristic, we use cross-validation. Cross-validation allows not only to validate with one testing set, but validates on many testing sets by shuffling all corridors into several training-testing splits. Thus, we split our 10 corridors into 8 corridors for training and 2 for testing. For all split combinations of 2 from 10, we solve the set covering problem using a greedy heuristic and test the representative weight vectors on the two test corridors.

SCP reduces clusters to a third of representative ones. Figure 3 shows the results of the SCP for each test corridor in average. The average is taken from all training splits where the corridor belongs to the testing group. The black line represents the average amount of clusters used for the training. The purple line shows the amount of representative weight vectors resulting from the SCP. GSS-WGR and OWT-RH have smaller count values, which can be explained by the fact that their high cluster amount does not contribute to the training clusters. We can see that the SCP allows to reduce on average the amount of clusters from 30 to 10 representative vectors. This allows to divide the computational time of the heuristic by three. Computing 10 instances through the heuristic instead of 2000 as in the framework reaches our goal of quick solving. The next step is to check whether these representative weight vectors actually cover the clusters.

Cluster coverage performs to 75%. Figure 4 presents the average cluster coverage performance of each test corridor, i.e. the amount of clusters found by the representative weight vectors divided by the total amount of clusters. The average is again taken from all training splits where the corridor belongs to the testing group. The test corridors are ranged by descending testing performance. The training performance is always 100% as the SCP is designed to cover all training clusters. The mean testing coverage performance is around 75%. SA-TW and GD-PR performs to 100% meaning that all clusters are found by the representative weight vectors. GSS-WGR and OWT-RH perform only with 60%, which can be explained by their high number of clusters to be covered. For example,

Figure 3: Average amount of training clusters (before SCP) and of representative weight vectors (after SCP) for each test corridor.

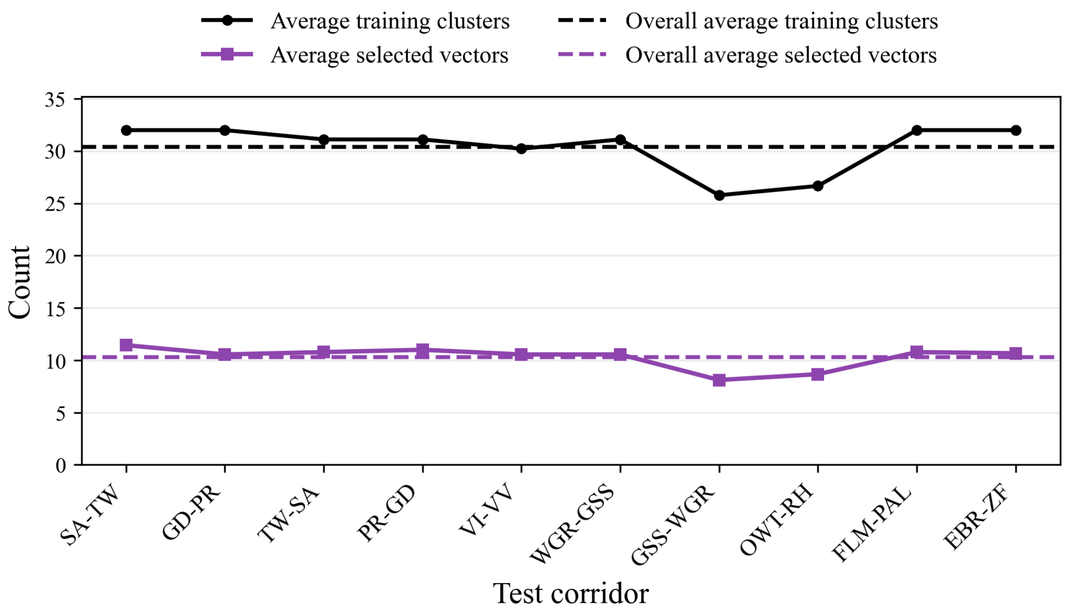
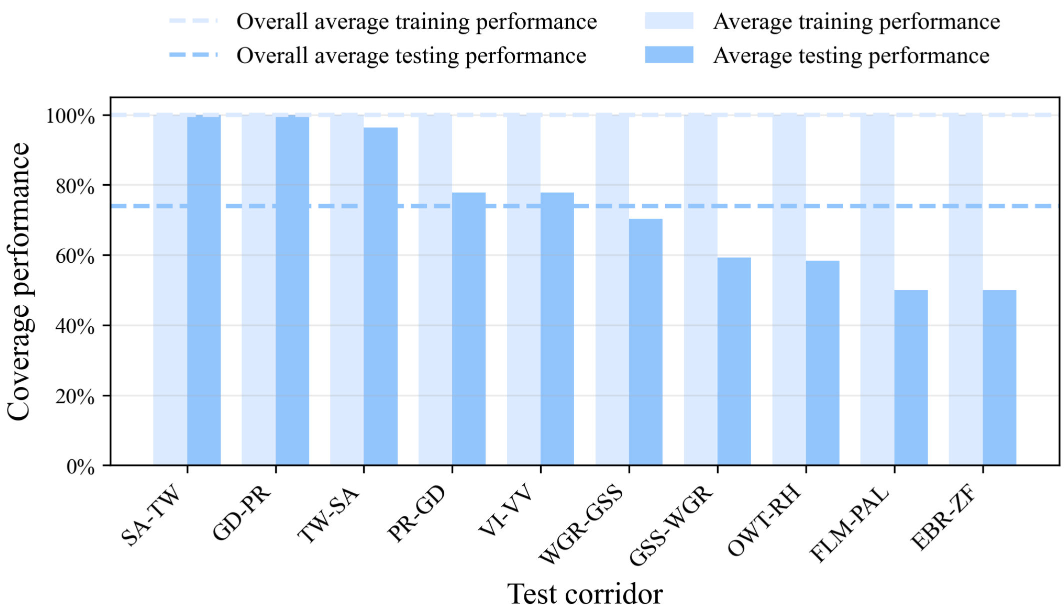


Figure 4: Training and testing cluster coverage performances for each test corridor.



GSS-WGR has 9 clusters to be found with a mean of only 8 representative weight vectors (see Figure 3). Finally, FLM-PAL and EBR-ZF have only one of their two clusters covered in average. This phenomenon is difficult to explain at this stage and should be further investigated. Despite these two exceptions, the heuristic performs well overall and has potential for generalization over several railway corridors.

7 Discussion

In this part, we will discuss limitations of the approach. A first point is the random generation of the weight vectors. We could use other distribution and more than 2000 random weight vectors to assess how well the solution space is represented. The clustering algorithm with the closeness and distance thresholds is also subject to discussion. Another approach than clustering could be to define solution groups based on the time-space structure. Moreover, in this SBB test case, the objective of deferment should be included in the analysis. Finally, a more precise analysis of the representativeness of the clusters by the vectors to understand the validity of the heuristic should be looked at.

8 Conclusion

This work aimed to provide a small, carefully chosen set of distinct solutions that performs well across a range of relevant objectives. To do so, we generated for each railway corridor two thousand solutions by optimizing with different objective weights. We managed to cluster these solutions based on the closeness of their own solutions and their distance to solution to other clusters. Thus, the solution space could be resumed as few and distinct solution clusters, where the cluster amount ranged from 1 to 9. We only considered the 10 corridors having more than 1 cluster for the next steps. Then, we proposed a heuristic to calculate distinct solutions quickly on new corridors. The set covering problem considering clusters of several corridors allowed to summarize to a third those into a few representative weight vectors. Finally, cross-validation shows heuristic performs to an average of 75% cluster coverage. Despite the exception of two test corridors, the generalization of the methodology seems promising. The framework successfully delivers representative objective weights for the heuristic to calculate quickly a small set of distinct solutions. As a next step, different weight vector generation, clustering and set covering problem approaches should be explored to further improve the framework.

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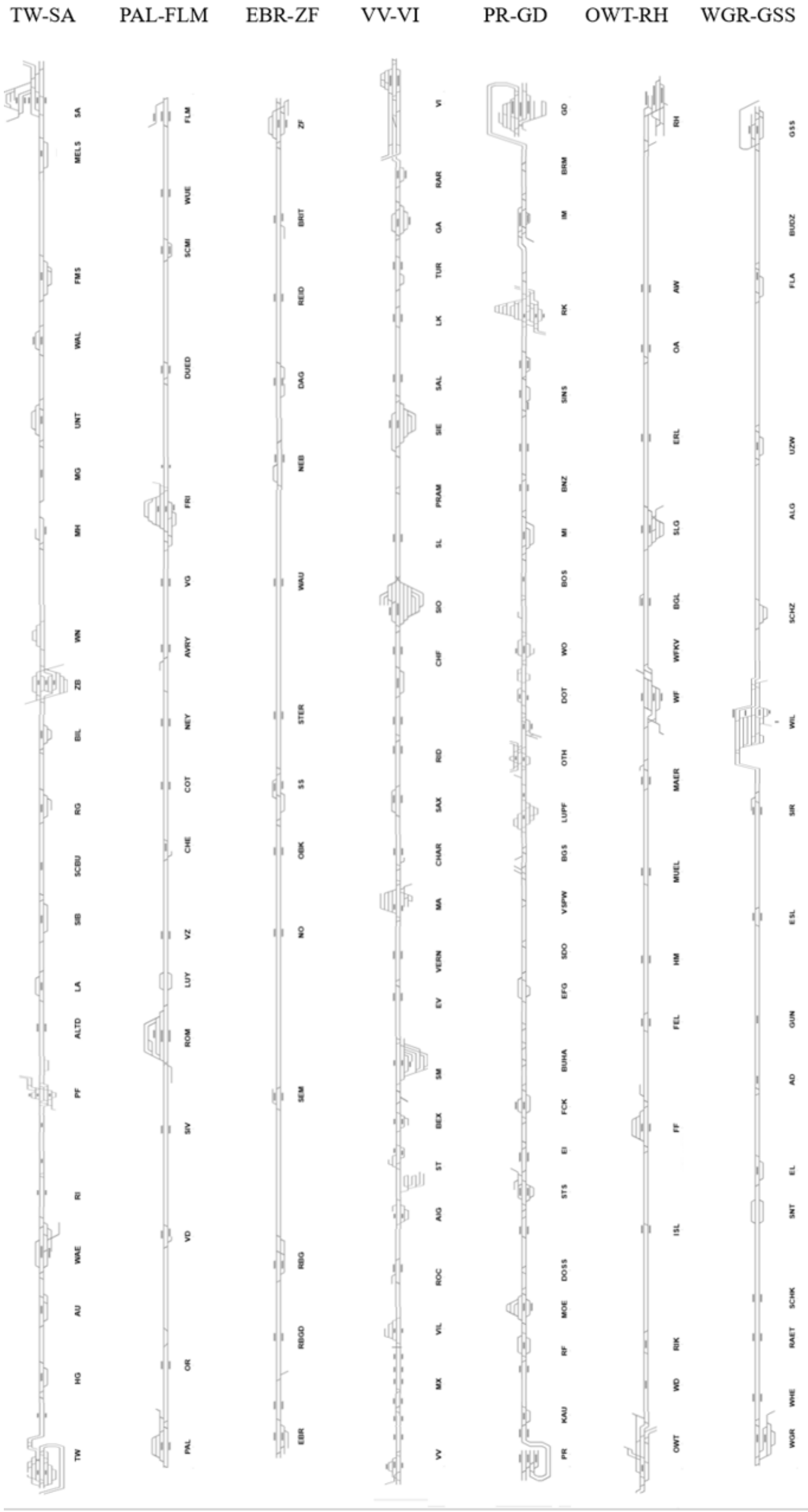
A SBB Corridors topologies



Source: SBB

B Clustering results: additional train path solutions

Time space diagram per corridor with all additional train path solutions by clusters.