

Dispatching-Area Design

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Abstract

Increasing traffic density and system interdependencies in railway networks can lead to imbalanced workload distribution among train dispatchers. Traditional dispatching-area design, often based on historical and geographical considerations, may no longer reflect current infrastructure complexity and coordination requirements, potentially affecting punctuality and operational robustness.

In this paper, we study the problem of partitioning a set of train stations into a predefined number of dispatching areas, formulated as a multi-objective mixed-integer programming problem. The objective is to minimize a weighted sum of inter-area interaction complexity and intra-area operational complexity. Inter-area complexity captures coordination needs through the number of trains crossing area boundaries, while intra-area complexity is modeled using station-related parameters, including track layout, traffic density, starting and ending services, and traffic heterogeneity (mix of passenger and freight traffic).

We apply the suggested approach to instances from the Malmö dispatching center in the southern part of the Swedish railway network, illustrating how an optimization-grounded sectorization framework can support structured and balanced redesign of dispatching areas. We evaluate the model's robustness by through sensitivity analyses on objective weights, minimum area size, and the number of dispatching areas. These analyses provide insights into how different planning priorities influence the resulting sectorization.

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1 Introduction

A railway network is divided into smaller regions corresponding to different parts of a country, each supervised by a dispatching center. In turn, each region is further subdivided into dispatching areas managed by individual dispatchers to ensure safe and efficient traffic flows. An area may include one or several stations, such as a passenger station, a freight terminal, or simply a section of track equipped with switches. Historically, an area corresponds to a major station together with small adjacent ones. However, an increase in traffic demand, timetable density, and system interdependency may significantly impact the workload level and its distribution over time and across the network. The consequence is that some areas may experience a high traffic density with many conflicting train paths, while others are quite simple to manage. Such imbalanced area design has a direct impact on workload distribution between train dispatchers, potentially affecting punctuality and operational robustness.



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To address this issue, infrastructure managers aim to redesign operational areas taking into account station complexity, traffic flows between stations, and spatial coherence. The objective is to distribute operational complexity more evenly while maintaining spatial continuity. A balanced area design supports decision making, improves disturbance handling, and contributes to more efficient utilization of human resources.

Partitioning a network into sectors, often called sectorization, can be viewed as a graph partitioning problem. In this paper, we suggest a framework for partitioning a railway network, given as a set of stations, into a predefined number of dispatching areas (sectors). We apply the suggested model on instances from the Malmö dispatching center, which is responsible for the southern part of the Swedish railway network. Today, the considered network is divided into about 15 areas. The present structure has evolved gradually over several decades and originates from an early organization based primarily on historically important main stations. Our goal is to improve the area design based on the actual traffic demand and infrastructure complexity. The contributions of this work are to propose a relatively simple optimization model that supports design as well as redesign of dispatching areas.

Related Work. Sectorization (also called distriction or territory design) is the process of partitioning a larger area into smaller units according to defined goals while satisfying given constraints [13]. Such problems arise in many practical contexts, including electoral districting [3], road-traffic control [6], maintenance-service areas [11], school [7] and healthcare zoning [2], police-coverage planning [4], and air-traffic-control operations [19]. The goal of sectorization is to create manageable working sectors, in terms of workload, while certain constraints are fulfilled [13]. Typical examples of these constraints include equilibrium (balanced area, demand, workload, etc.), compactness (dense sector shape), contiguity (sector convexity), capacity (upper bound), boundary (certain basic units must belong to different sectors) and neighborhood (certain basic units must belong to the same sector). In air-traffic control, a field with many similarities to train dispatching, researchers showed that the workload of a traffic controller depends not only on the number of aircraft in a sector, but rather on their dynamic characteristics, their routes, and their interaction with each other [5]. Sridhar et al. [14] defined airspace complexity through (i) structural features – fixed geometry like airways and intersections –, and (ii) flow complexity – dynamic aspects such as aircraft numbers and interactions. Gianazza [8] suggested a data-driven model for air-traffic-control sectorization based on workload. The explanatory variables in their model included the sector size, number of aircraft within a sector and their average absolute vertical speed, incoming flow, and the number of speed vector intersections (with an angle greater than 20 degrees). Yousefi and Donohue [17] proposed an integer-programming method to improve static airspace sectorization by balancing controller workload. They divided the airspace into hexagonal cells, estimated each cell’s workload through simulation, and then applied an integer-programming-based clustering algorithm to group the cells into sectors with similar overall workload levels. Mitchell et al. [12] examined dynamic airspace design using computational geometry to create sectors that evenly distribute controller workload over time, rather than depending on static boundaries. Xue [16] proposed a two-step approach to sectorize airspace. The first step, consists in generating initial sectors based on Voronoi diagrams, and then a genetic algorithm is used to fine-tune the sectors’ boundaries while optimizing the performance (low coordination between sectors) and balancing workload. Granberg et al. [9] presented a mixed-integer-program (MIP) framework for airspace sectorization in terminal maneuvering areas, incorporating airspace complexity and geometric constraints to support effective conflict management.

Sectorization of train-dispatching areas has been addressed by several researchers. Zhao et al. [18] formulated the train dispatcher desk districting problem as a MIP to create contiguous, feasible, and workload-balanced districts while minimizing inter-desk coordination. In their approach, they balance workload by minimizing the deviation between districts' workload and an average workload value. The workload is estimated using proxies based on section length and train movements, including the number of trains traveling through sections and stopping at stations. In contrast, in the present study we focus on districting stations while omitting the explicit assignment of track sections, which can subsequently be handled through operational rules of thumb, such as dividing sections at their midpoint. Furthermore, workload estimation in our study is based on a weighted combination of five operational characteristics: track-layout complexity, traffic density, starting and ending services, traffic heterogeneity in terms of passenger and freight traffic mix, and inter-areas flow. Instead of minimizing workload deviations from a single average value – not well suited to either our approach or our data – we propose different workload balancing strategies depending on the specific type of workload being considered. To solve instances for a real high-speed railway network, Zhao et al. [18] needed an iterative-search-based heuristic, which resulted in a total computation time below 33 minutes. Wang et al. [15] addressed the same problem as Zhao et al. [18] and generalized it from a railway-dispatcher-specific formulation to a general simultaneous node-and-link districting problem, using column generation and a hybrid exact–heuristic framework to yield near-optimal or optimal solutions for most instances.

In general, sectorization/districting problems are NP-hard [1, 10]. In our approach, we propose an exact method based on a MIP formulation. We formulate the dispatching-area design problem as a multi-objective optimization problem due to its conflicting criteria and use scalarization methods to explore the Pareto-optimal solution space. Since the practical requirements neither impose strict area connectivity (traffic is allowed to leave and re-enter an area) nor the compactness of the areas (given the eel-like shape of the network), we can use a simplified model structure. As a result, we solve real-world instances to optimum or near optimum within acceptable computational times.

The remainder of this paper is organized as follows. In Section 2, we formulate the problem statement. In Section 3, we present the MIP formulation. In Section 4, we describe the experimental setup. In Section 5, we present and analyze the results. Finally, in Section 6, we conclude with future work and recommendations.

2 Problem Statement

Our sectorization problem consists of determining an optimal partition of a set of train stations S into a set of areas A with a predefined cardinality. The problem statement of our dispatching-area-design is as follows:

Given: A set of train stations; a set of adjacent station-pairs; the number of train tracks, movements, and starting and ending train services in each station, as well as the corresponding maximum values among all stations; the number of crossing train movements between each pair of stations; a set of trains operating in the network; a list of trains visiting each station and the number of yearly movements for each train; the number of passenger and freight trains in each station per year; a list of factor weights representing the priorities between the objectives; and a predefined number of areas representing dispatching sectors.

Find: an area partition of the stations into a predefined number of areas such that each station is assigned to exactly one area, inter-area interaction, measured by area-crossing train flows, is minimized, and the resulting intra-area workloads are as balanced as possible.

Workload balance is achieved by minimizing a weighted sum of deviations from predefined reference values, derived from the largest stations, for the total number of tracks in each area, the total number of starting and ending train services in each area, and the total number of train movements in each area. In addition, we promote traffic homogeneity within each area by encouraging each area to be dominated either by passenger trains or by freight trains.

3 Mathematical Formulation

We view the dispatching-area design problem as involving multiple, often conflicting, criteria. Improving one aspect of the design may negatively affect another – for example, reducing inter-area complexity may increase intra-area workload. We therefore formulate the problem as a multi-objective optimization problem, aiming to characterize the trade-offs between the two competing criteria: the complexity within areas and the complexity of inter-area interactions.

The complexity within areas is determined by the complexities of the stations assigned to each area. Each station i is associated with parameters representing its complexities, captured by (i) the number of tracks in the station, (ii) the number of starting and ending train lines, (iii) the number of unique trains visiting the station, and (iv) the heterogeneity of the traffic (passenger versus freight trains). The inter-area interaction complexity is determined by the number of trains flowing from one area j to another. The objective is to find a partition of with the lowest total cost, defined as a convex combination of the complexity factors within each area and the complexity of inter-area interactions.

We model the problem as a MIP:

$$\text{minimize} \quad \sum_{k=1}^5 \alpha_k \cdot \frac{f_k - f_k^{min}}{\bar{f}_k - f_k^{min}} \quad (1)$$

subject to:

$$\sum_j y_{i,j} = 1 \quad \forall i \in S \quad (2)$$

$$f_5 = \sum_{\{i,i'\} \in E} p_{i,i'} \cdot m_{i,i'} \quad (3)$$

$$y_{i,j} - y_{i',j} \leq p_{i,i'} \quad \forall j \in A, \forall \{i,i'\} \in E \quad (4)$$

$$y_{i',j} - y_{i,j} \leq p_{i,i'} \quad \forall j \in A, \forall \{i,i'\} \in E \quad (5)$$

$$\sum_i \ell_{i,k} \cdot y_{i,j} - \ell_k^{max} \leq f_k \quad \forall j \in A, \forall k \in \{1, 2\} \quad (6)$$

$$\ell_k^{max} - \sum_i \ell_{i,k} \cdot y_{i,j} \leq f_k \quad \forall j \in A, \forall k \in \{1, 2\} \quad (7)$$

$$t_{j,n}^{ar} \geq y_{i,j} \cdot t_{i,n}^{st} \quad \forall j \in A, \forall n \in T \quad (8)$$

$$t_{j,n}^{ar} \leq \sum_i y_{i,j} \cdot t_{i,n}^{st} \quad \forall j \in A, \forall n \in T \quad (9)$$

$$t_{max} - \sum_n t_{j,n}^{ar} \cdot t_n \leq f_3 \quad \forall j \in A \quad (10)$$

$$\sum_i y_{i,j} \cdot m_i^p \leq f_4 + M \cdot z_j \quad \forall j \in A \quad (11)$$

$$\sum_i y_{i,j} \cdot m_i^f \leq f_4 + M \cdot (1 - z_j) \quad \forall j \in A \quad (12)$$

$$y_{i,j} \in \{0, 1\} \quad \forall i \in S, j \in A \quad (13)$$

$$p_{i,i'} \in \{0, 1\} \quad \forall \{i, i'\} \in E \quad (14)$$

$$t_{j,n}^{ar} \in \{0, 1\} \quad \forall j \in A, n \in T \quad (15)$$

$$z_j \in \{0, 1\} \quad \forall j \in A \quad (16)$$

$$f_k \in \mathbb{R}^+ \quad \forall k \in \{1, 2, 3, 4, 5\} \quad (17)$$

The main decision variable is the binary $y_{i,j}$, which assigns a station i to area j whenever $y_{i,j} = 1$. The variable f_k (with $k \in \{1, 2, 3, 4, 5\}$) is used to determine the workload balance for each workload factor. We present more details on the variables and parameters used in the model in Table 1.

The first constraint (2) assures that each station is assigned to exactly one area. Constraint (3) defines the fifth component of the objective value, f_5 , which represents the total number of train movements between areas. Constraints (4) and (5) activate the variable $p_{i,i'}$ whenever stations i and i' are assigned to different areas, which would result in a penalization, in the objective function, by a weight factor $m_{i,i'}$ corresponding to the train movements between the adjacent station pair $\{i, i'\}$. Here, $\{i, i'\}$ denotes an element of the set of edges E in the adjacency graph. This component of the objective function is represented by f_5 . Constraints (6) and (7) define the variables f_1 and f_2 as upper bounds on the deviation of the area workloads from their respective maxima, where ℓ_1^{max} and ℓ_2^{max} denote the maximum number of tracks and the maximum number of starting and ending train services in a station, respectively. These parameters, ℓ_1^{max} and ℓ_2^{max} , are derived from observations at large stations, such as Malmö Central. Minimizing deviations from these workload values promotes a balanced allocation of workload across areas. Since high workload levels are typically associated with large stations assigned to specific areas, balancing the workload may require aggregating smaller stations into other areas to reduce workload disparities.

Balancing the number of train movements between areas is achieved by minimizing the deviation between the number of trains (from the set of trains T indexed by n) visiting each area and the maximum number of trains, t_{max} , observed at a station, typically a large one. This deviation's upper bound is determined by the variable f_3 (see Constraint (10)). We use Constraints (8) and (9) to determine the binary variable $t_{j,n}^{ar}$ for whether a train n visited an area j , based on whether the train n visited a station i assigned to the area j .

Given that we aim for traffic that is as homogeneous as possible – that is, areas dominated either by passenger trains or by freight trains – we introduce the integer variable f_4 , representing an upper bound on the minimum number of passenger (m_j^p) or freight (m_j^f) trains across all areas (see Constraints (11) and (12)). By minimizing f_4 , the model seeks to reduce the smaller of the two traffic types within each area. Consequently, stations with relatively low numbers of either passenger or freight trains are encouraged to be grouped into the same area, leading to areas that are more clearly dominated by a single traffic type and therefore more homogeneous. Furthermore, we define the binary variable z_j , which takes the value 1 if area j contains more passenger trains than freight trains, and 0 otherwise.

The objective function is defined as a convex combination of the weighted complexity measures, where the weights are denoted by α_k ($k \in [1, 2, 3, 4, 5]$). Since the complexity measures differ substantially in scale and units, each objective term is normalized by its attainable range. Specifically, the k -th objective is normalized as: $\frac{f_k - f_k^{min}}{f_k - f_k^{min}}$, where f_k^{min} denotes the minimum attainable value of the corresponding k -th complexity measure, and $\bar{f}_k$ denotes the maximum obtained value when each of the other objectives is individually minimized; a detailed definition of these values is provided in Subsection 5.1. By this normalization we ensure that all objective components contribute on a comparable scale, and that the total objective value is in the range $[0, 1]$.

■ **Table 1** Description of the model's variable and parameters.

Notation	Type	Description
$y_{i,j}$	var (binary)	=1 if station i is assigned to area j
$p_{i,i'}$	var (binary)	=1 if adjacent stations i and i' are assigned to different areas
f_1	var	max deviation of the number of tracks from the max
f_2	var	max deviation of the number of starting/ending services from the max
f_3	var	max deviation of the number of train movements from the max
f_4	var	max-min of either passenger or freight trains across all areas
f_5	var	total number of crossing train movements between areas
$t_{j,n}^{ar}$	var(binary)	=1 if train n visits area j
z_j	var (binary)	=1 if area j contains more passenger than freight trains
S	set	set of train stations (indexed by i)
A	set	set of areas (indexed by j)
T	set	set of trains (indexed by n)
$m_{i,i'}$	param	number of trains movements between adjacent stations i and i'
$\ell_{1,i}$	param	total number of tracks in station i
$\ell_{2,i}$	param	total number of starting/ending services in station i
ℓ_1^{max}	param	maximum number of tracks in a large station
ℓ_2^{max}	param	maximum number of starting/ending services in a large station
t_{max}	param	maximum number of train movements in a large station
t_n	param	number of movements for train n
$t_{i,n}^{st}$	param (binary)	=1 if train n visits station i
m_i^p	param	number of movements of passenger trains visiting station i
m_i^f	param	number of movements of freight trains visiting station i
α_1	param	cost associated with the number of tracks in areas
α_2	param	cost associated with the number of starting/ending trains in areas
α_3	param	cost associated with the number of train movements in areas
α_4	param	cost associated with the traffic homogeneity in areas
α_5	param	cost associated with inter-area-crossing train movements
M	param	a big number; given by $\max(\sum_i m_i^f; \sum_i m_i^p)$

4 Experiment Setup

We consider the railway network controlled by the Malmö dispatching center, which covers the southern region of Sweden. The network comprises 178 operation points (*driftplatser* in Swedish), including switches, stations, and shunting areas. For simplicity, we refer to all operation points as stations throughout this paper.

The available data include route information and the annual train timetable for 2026, specifying train IDs, train types (passenger or freight), arrival and departure times at each station, and service frequencies. In addition, data on the number of tracks at each station were provided. Based on these data, we derived the parameters $m_{i,i'}$, $\ell_{1,i}$, $\ell_{2,i}$, t_n , $t_{i,n}^{st}$, m_i^p , and m_i^f . For the workload data representing a large station, the maximum numbers of train movements, tracks, and starting/ending train services were set to $t_{max} = 299020$, $\ell_1^{max} = 27$, and $\ell_2^{max} = 170024$, respectively. Both t_{max} and ℓ_2^{max} were obtained at Malmö Central Station (Mc), whereas ℓ_1^{max} occurred at Malmö Godsbangård (Mgb).

Before conducting our experiments, and to reduce the domain size and break symmetries, we introduce several additional constraints to the MIP formulation. The first group of constraints restricts the assignment of stations to areas based on their geographical location.

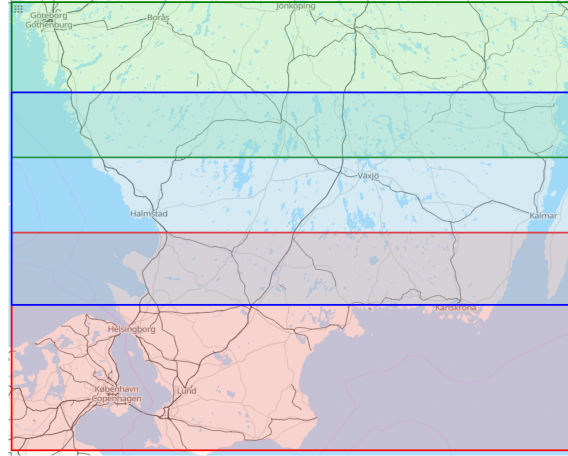
We begin by partitioning the network into three regions: south, middle, and north. Stations in the southern region are prohibited from being assigned to areas 7–14 and may therefore only be assigned to areas in the interval $[0,6]$. Similarly, stations in the middle and northern regions may only be assigned to areas in the intervals $[6,9]$ and $[9,14]$, respectively. Note that we allow some overlap between the admissible area assignments of adjacent regions to provide additional flexibility. We denote the sets of prohibited area assignments by $\overline{A}_s$, $\overline{A}_m$, $\overline{A}_n$ (the complements of the allowed area assignments) for the south, middle, and north, respectively.

Based on their coordinates, we partition the stations into three subsets, S_s , S_m , and S_n , which denote stations in the south, middle and north, respectively. In Figure 1, we illustrate the geographical boundaries of the regions corresponding to S_s , S_m , and S_n . The first group of additional constraints are:

$$\sum_{i \in S_s} y_{i,j} = 0 \quad \forall j \in \overline{A}_s \quad (18)$$

$$\sum_{i \in S_m} y_{i,j} = 0 \quad \forall j \in \overline{A}_m \quad (19)$$

$$\sum_{i \in S_n} y_{i,j} = 0 \quad \forall j \in \overline{A}_n \quad (20)$$



■ **Figure 1** Partition of the network into the three regions, south (red), middle (blue), and north (green).

To further reduce symmetry within each geographical region, we fix the assignments of a small number of major stations to specific areas within their respective admissible area subsets. These fixed assignments serve as anchor points and eliminate equivalent solutions that differ only by permutations of area labels within a region.

Finally, we introduce a third constraints group to prohibit assignments of station pairs to the same area if these stations are located too far from each other. The assumed reference distance is 160 km, which refers to the distance between Kalmar and Rimforsa. This assumption is based on a simple calculation: the total area under study covers approximately $60\,000 \text{ km}^2$, so dividing by the number of areas ($n = 15$) gives an average area of $60\,000/15 = 4\,000 \text{ km}^2$. A circle enclosing this area would have a diameter of $d = 2\sqrt{4000/\pi} \approx 71 \text{ km}$. Since a circle minimizes the maximum internal distance for a given area, this value is a lower bound: any less regular area shape will have a larger diameter. Our threshold of 160 km is more than double this reference value, leaving sufficient margin for irregular area shapes,

or larger areas, while still excluding implausible groupings of distant stations. We generate the binary parameter $d_{i,i'}$ that is equal to 1 if the distance between the stations i and i' is greater than the threshold distance. The new additional constraints are:

$$d_{i,i'} \cdot (y_{i,j} + y_{i',j}) \leq 1 \quad \forall j \in A, \forall i \in S, \forall i' \in S \quad (21)$$

We believe that our assumptions, within the added constraints, are reasonable and not overly restrictive. Large stations are unlikely to be assigned to the same area except in very poor solutions, as such assignments would result in poor objective values with respect to both inter- and intra-area measures. In contrast, we acknowledge that prohibiting the assignment of certain geographically distant station pairs to the same area could affect the intra-area workload. However, such assignments would correspond to operationally undesirable solutions and are therefore unlikely to be of practical interest in the dispatching context.

To model and solve our MIP, we employ the Python programming language together with the Gurobi solver (version 12.0.3). The stopping criteria are either a runtime limit of 24 hours or achieving an optimality gap of 1%. The computational experiments are carried out on a high-performance Sigma server (2019), equipped with Intel Xeon Gold 6130 nodes featuring 32 CPU cores and 384 GiB of memory, provided by the National Academic Infrastructure for Supercomputing in Sweden (NAISS).

5 Computational Results

In this section, we present the results of our experiments. We begin with the normalization step, as our multiobjective model involves objectives with different units and scales. We then examine the impact of varying different MIP parameters in the remaining experiments.

5.1 Normalization of the Objective Value

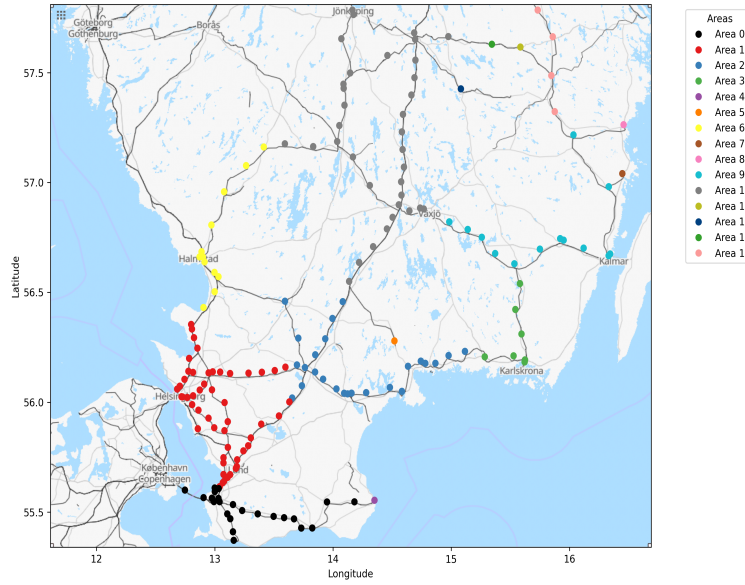
Before the experiments, we normalize the objective function by determining the minimum and maximum attainable values, f_k^{min} and $\bar{f}_k$. We obtain f_k^{min} by solving the MIP for the k -th objective alone, setting its weight to 1 and all others to 0. The resulting objective values and other complexity measures are reported in Table 2. Each instance is denoted by $I_{\alpha_1;\alpha_2;\alpha_3;\alpha_4;\alpha_5}$, where α_k is the weight of the k -th objective term. We define $\bar{f}_k$ as the highest value of the k -th objective across all instances. The last column reports the number of disconnected and large areas. An area is disconnected if the subgraph induced by its stations is disconnected. Although such areas can be operationally feasible – e.g., when a large station belongs to one area and stations on several outgoing lines to another – widely separated connected components are undesirable. We therefore track disconnected areas throughout the experiments.

An area is considered large if it contains at least five stations. Although small areas are acceptable, they are generally less desirable. These characteristics are not explicitly controlled but emerge from the optimization. Thus, reducing disconnected and small areas, particularly those interrupted by multiple other areas, would improve solution quality.

The resulting runtime for all instances was below 23 seconds. The minimum number of tracks is $f_1^{min} = 27$, obtained for the area containing only the Mgb station, a marshaling yard near Malmö. When targeting inter-area flow, all other objectives reach their $\bar{f}_k$ values, showing a clear trade-off between inter- and intra-area complexities. This is further evident from the inter-area-flow values, which are equal to $\bar{f}_5$ for all instances except the last, where this objective is explicitly targeted. Moreover, minimizing inter-area flow results in fully connected areas, as reducing area-border-crossing flows lowers the penalty cost. However, this

■ **Table 2** Normalization results, including runtime (in seconds), objective values f_1 (tracks), f_2 (start-/end train services), f_3 (train movements), f_4 (freight/passenger train movements), f_5 (total inter-area flows), and the number of disconnected and large areas (D;L). $f_k^{\min}$ and $\bar{f}_k$ are in bold.

instance	r (s)	obj	f_1 (track)	f_2 (st/end)	f_3 (mov)	f_4 (m^f/m^p)	f_5 (inter-flow)	#D;L areas
$I_{1;0;0;0;0}$	22	27	27	170024	286612	1088157	7040596	12;12
$I_{0;1;0;0;0}$	15	162647	80	162647	257476	1631859	7040596	14;12
$I_{0;0;1;0;0}$	23	233629	76	169099	233629	1446174	7040596	14;13
$I_{0;0;0;1;0}$	20	109310	38	166579	287412	109310	7040596	14;13
$I_{0;0;0;0;1}$	12	479297	153	170024	298608	3521680	479297	0;8
		$f_k^{\min}$	27	162647	233629	109310	479297	
		$\bar{f}_k$	153	170024	298608	3521680	7040596	



■ **Figure 2** Solution for Instance $I_{0;0;0;0;1}$. The colored dots denote station-area assignments.

connectivity comes at the cost of extreme imbalances in the intra-area measures. Figure 2 illustrates the partition obtained for Instance $I_{0;0;0;0;1}$, highlighting the imbalance in area sizes, with only eight areas being large. This occurs because the solver tends to merge as many neighboring stations as possible into large areas, leaving a small number of stations in smaller areas that only satisfy the partition's cardinality constraint.

5.2 Equal Weights for all Objectives

Now that the objectives are normalized, we proceed with several experiment sets. We first assign equal weights to all objectives. The remaining sets investigate the impact of changing the objectives' weights (Subsections 5.3 and 5.4), restricting area size (Subsection 5.6), and reducing the number of areas (Subsection 5.7).

In the first set, all objectives are assigned equal weights ($\alpha_k = \frac{1}{5}$, $\forall k$). We report the results in the first row in Table 3. For each obtained objective component f_k , we report a percentage value that measures its relative position within the range defined by $f_k^{\min}$ and $\bar{f}_k$.

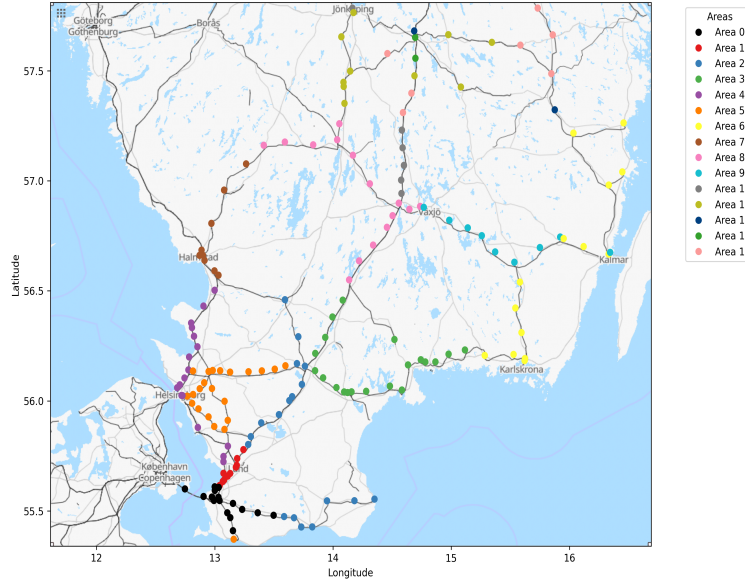
■ **Table 3** Results for decreasing and increasing some targeted weights.

instance	r (m)	obj 10^{-3}	f_1 (track)	f_2 (st/end)	f_3 (mov)	f_4 (m^f/m^p)	f_5 (inter-flow)	#D;L areas
$I_{\frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}}$	137	34	33 5%	162647 0%	233640 0%	169841 2%	1173462 11%	10;13
$I_{\frac{4}{400}, \frac{99}{400}, \frac{99}{400}, \frac{99}{400}, \frac{99}{400}}$	50	27	53 21%	162647 0%	233640 0%	163051 2%	1035703 8%	8;13
$I_{\frac{99}{400}, \frac{4}{400}, \frac{99}{400}, \frac{99}{400}, \frac{99}{400}}$	120	42	33 5%	162859 3%	233640 0%	169841 2%	1161709 10%	9;13
$I_{\frac{99}{400}, \frac{99}{400}, \frac{4}{400}, \frac{99}{400}, \frac{99}{400}}$	296	32	27 0%	162647 0%	266063 50%	163880 2%	1097347 9%	6;13
$I_{\frac{99}{400}, \frac{99}{400}, \frac{99}{400}, \frac{4}{400}, \frac{99}{400}}$	7	43	35 6%	162647 0%	233640 0%	300646 6%	1129301 10%	9;13
$I_{\frac{99}{400}, \frac{99}{400}, \frac{99}{400}, \frac{99}{400}, \frac{4}{400}}$	11	14	33 5%	162647 0%	233629 0%	118258 0%	1741982 19%	14;13
$I_{\frac{156}{400}, \frac{61}{400}, \frac{61}{400}, \frac{61}{400}, \frac{61}{400}}$	83	38	33 5%	162647 0%	233640 0%	169841 2%	1182046 11%	9;13
$I_{\frac{61}{400}, \frac{156}{400}, \frac{61}{400}, \frac{61}{400}, \frac{61}{400}}$	65	26	33 5%	162647 0%	233640 0%	169841 2%	1173462 11%	9;13
$I_{\frac{61}{400}, \frac{61}{400}, \frac{156}{400}, \frac{61}{400}, \frac{61}{400}}$	53	26	33 5%	162647 0%	233640 0%	161285 2%	1201512 11%	9;13
$I_{\frac{61}{400}, \frac{61}{400}, \frac{61}{400}, \frac{156}{400}, \frac{61}{400}}$	116	29	33 5%	162647 0%	233640 0%	133680 1%	1294482 12%	10;13
$I_{\frac{61}{400}, \frac{61}{400}, \frac{61}{400}, \frac{61}{400}, \frac{156}{400}}$	91	49	35 6%	162647 0%	233640 0%	235693 4%	1047763 9%	8;13

Comparing each resulting objective component with its corresponding f_k^{min} for $k \in [1, \dots, 5]$, we observe percentage increases of 5%, 0%, 0%, 2%, and 11%, respectively. The increase in inter-area flow is relatively larger than that in intra-area imbalance, which is practically negligible – particularly for f_2 and f_3 , which retain their optimal values. This suggests that the first four components drive the solution consistently toward improved intra-area balance. Furthermore, the resulting partition contains 10 disconnected areas, which remains relatively high given that only the inter-area flow component (f_5) promotes connectivity. Figure 3 illustrates the resulting partition, highlighting both the variation in the number of stations per area and the appearance of disconnected components.

5.3 Decreasing One of the Weights

In this set, we vary the objective weights by reducing one to a low value (0.01) while keeping the others equal. To preserve the convexity of the weighted sum, the remaining weights are increased by $\frac{\delta}{4}$, where δ is the deviation from the initial value $\frac{1}{5}$. For example, reducing the first weight gives $[\frac{1}{5} - \delta; \frac{1}{5} + \frac{\delta}{4}; \frac{1}{5} + \frac{\delta}{4}; \frac{1}{5} + \frac{\delta}{4}; \frac{1}{5} + \frac{\delta}{4}]$. Thus, the weights always sum to 1. To save space in the result tables, we denote instance weights as fractions rather than decimals, using a common denominator whenever possible to facilitate comparison. The results are reported in Rows 2–6 of Table 3.



■ **Figure 3** Solution using equal weights of $\frac{1}{5}$ for all objective components.

Comparing each objective component across instances with its corresponding f_k^{min} , we observe that all components increase when their associated weight α_k is the smallest. However, some components – namely f_1 , f_4 and f_5 – exhibit greater variability across instances, whereas f_2 , f_3 retain their f_k^{min} values in most cases, except when their corresponding weights are the smallest. Moreover, f_1 , f_3 and f_5 experience the largest deviations (+21%, +50%, and +19%, respectively) from their respective f_k^{min} values when their associated weight α_k is the smallest, while f_2 and f_4 remain comparatively close to their minimum values. These observations help identify the objective components that are most sensitive to reductions in their assigned weights and therefore the most relevant for the upcoming experiments.

In the last column, the number of disconnected areas is relatively low for all instances except the last one, $I_{\frac{99}{400}; \frac{99}{400}; \frac{99}{400}; \frac{99}{400}; \frac{4}{400}}$, which has 14 disconnected areas. This suggests that assigning a low weight to f_5 leads to more disconnected areas. Comparing the objective component f_5 for the equal-weight instance $(I_{\frac{1}{5}; \frac{1}{5}; \frac{1}{5}; \frac{1}{5}; \frac{1}{5}})$ with the other instances, we observe that f_5 improves whenever an intra-area weight is decreased, while it increases only when α_5 is decreased. This confirms the trade-off between inter- and intra-area workloads.

5.4 Increasing One of the Weights

We adopt the same methodology as in Subsection 5.3, but increase one weight at a time instead of decreasing it, while keeping the same deviation value, $\delta = 0.19$. Emphasizing the first objective yields the weight vector $[0.2 + \delta; 0.2 - \frac{\delta}{4}; 0.2 - \frac{\delta}{4}; 0.2 - \frac{\delta}{4}; 0.2 - \frac{\delta}{4}] = [0.39; 0.1525; 0.1525; 0.1525; 0.1525]$, expressed in fractional form as $[\frac{156}{400}; \frac{61}{400}; \frac{61}{400}; \frac{61}{400}; \frac{61}{400}]$. We report the results in the last five rows of Table 3.

Using instances $(I_{\frac{1}{5}; \frac{1}{5}; \frac{1}{5}; \frac{1}{5}; \frac{1}{5}})$ as a reference, almost all intra-area objective components remain stable. The exceptions are f_1 and f_4 in the last instance, $(I_{\frac{61}{400}; \frac{61}{400}; \frac{61}{400}; \frac{61}{400}; \frac{156}{400}})$, showing a relatively larger increase. In the same instance, f_5 improves as its weight α_5 increases, accompanied by a reduction in the number of disconnected areas, confirming the effect of assigning a higher weight to inter-area flow on maintaining area connectivity. However, the number of large areas remains unchanged across all instances, indicating that this factor is not directly influenced by any of the considered objectives.

To manage the trade-off between inter- and intra-area objectives, the following experiments retain only the most representative intra-area objectives. Based on the results presented above, we set a very low value for the weights α_2 and α_4 and keep only the objectives f_1 and f_3 as representative components of the inter-area objectives.

5.5 The Trade-off between Intra-Area and Inter-Area Objectives

In this experiment set, we retain objectives f_1 , f_3 , and f_5 , setting the weights of the remaining intra-area objectives to 0.01. We begin by assigning equal importance to intra- and inter-area objectives, yielding the weight vector $[\frac{24}{100}; \frac{1}{100}; \frac{24}{100}; \frac{1}{100}; \frac{50}{100}]$. For subsequent instances, we gradually increase α_5 while preserving convexity of the weighted sum, aiming to improve inter-area interaction until full connectivity is achieved across all areas. This approach highlights the trade-off between intra-area workload balance and inter-area connectivity. We report results in Table 4, including percentage scores of the objective components relative to their respective $f_k^{\min}$ and f_k .

■ **Table 4** Results using the weight vector: $[\alpha_1, 0.01, \alpha_3, 0.01, \alpha_5]$, where we gradually increase α_5 against α_1 and α_3 .

instance	r (m)	obj 10^{-3}	f_1 (track)	f_2 (st/end)	f_3 (mov)	f_4 (m^f/m^p)	f_5 (inter-flow)	#D;L areas
$I_{\frac{24}{100}; \frac{1}{100}; \frac{24}{100}; \frac{1}{100}; \frac{50}{100}}$	18	55	35 6%	162889 3%	233640 0%	296445 5%	994792 8%	8;14
$I_{\frac{19}{100}; \frac{1}{100}; \frac{19}{100}; \frac{1}{100}; \frac{60}{100}}$	110	60	35 6%	162889 3%	233640 0%	296445 5%	994792 8%	8;13
$I_{\frac{14}{100}; \frac{1}{100}; \frac{14}{100}; \frac{1}{100}; \frac{70}{100}}$	177	65	35 6%	162889 3%	233640 0%	296445 5%	994793 8%	8;13
$I_{\frac{9}{100}; \frac{1}{100}; \frac{9}{100}; \frac{1}{100}; \frac{80}{100}}$	197	69	35 6%	162889 3%	233928 0%	296445 5%	989691 8%	8;14
$I_{\frac{4}{100}; \frac{1}{100}; \frac{4}{100}; \frac{1}{100}; \frac{90}{100}}$	128	72	59 25%	168227 76%	285503 80%	362536 7%	640258 2%	3;11
$I_{\frac{3}{200}; \frac{1}{100}; \frac{3}{200}; \frac{1}{100}; \frac{95}{100}}$	7	42	143 92%	170024 100%	298272 99%	412464 8%	498353 0%	0;9

In the first four instances, from $I_{\frac{24}{100}; \frac{1}{100}; \frac{24}{100}; \frac{1}{100}; \frac{50}{100}}$ to $I_{\frac{9}{100}; \frac{1}{100}; \frac{9}{100}; \frac{1}{100}; \frac{80}{100}}$, the objective components remain nearly identical, with small differences in total values mainly due to the weight settings. The number of disconnected areas is unchanged, while the number of large areas varies only slightly, from 13 to 14. Only when α_5 reaches $\frac{90}{100}$ do f_1 , f_2 , and f_3 increase substantially, accompanied by improved inter-area flow, confirming the expected trade-off between intra- and inter-area objectives. The homogeneity component, f_4 , is only marginally affected. In the final instance, $I_{\frac{3}{200}; \frac{1}{100}; \frac{3}{200}; \frac{1}{100}; \frac{95}{100}}$, all areas become connected, but at the cost of substantially higher f_1 , f_2 , and f_3 values and fewer large areas.

5.6 The Impact of Restricting the Area Size

Since the number of large areas is not directly steered in our MIP, we decide to add a new constraint that forces all areas to include at least five stations. The new constraint is:

$$\sum_i y_{i,j} \geq 5 \quad \forall j \in A \quad (22)$$

We keep this new constraint in all remaining experiments of this paper. We rerun the same instances reported in Table 4, this time including Constraint (22), and we present the corresponding results in Table 5.

■ **Table 5** Results using same instances (weights) as in Table 4 but with a lower bound on the number of stations per area (at least 5).

instance	r (m)	obj 10^{-3}	f_1 (track)	f_2 (st/end)	f_3 (mov)	f_4 (m^f/m^p)	f_5 (inter-flow)	#D;L areas
$I_{\frac{24}{100}; \frac{1}{100}; \frac{24}{100}; \frac{1}{100}; \frac{50}{100}}$	16	56	35 6%	162889 3%	233640 0%	296445 5%	1001658 8%	8;15
$I_{\frac{19}{100}; \frac{1}{100}; \frac{19}{100}; \frac{1}{100}; \frac{60}{100}}$	53	60	35 6%	162889 3%	233640 0%	296445 5%	1001657 8%	8;15
$I_{\frac{14}{100}; \frac{1}{100}; \frac{14}{100}; \frac{1}{100}; \frac{70}{100}}$	223	65	35 6%	162889 3%	233640 0%	296445 5%	1001657 8%	8;15
$I_{\frac{9}{100}; \frac{1}{100}; \frac{9}{100}; \frac{1}{100}; \frac{80}{100}}$	354	70	35 6%	162889 3%	233928 0%	296445 5%	996219 8%	8;15
$I_{\frac{4}{100}; \frac{1}{100}; \frac{4}{100}; \frac{1}{100}; \frac{90}{100}}$	96	72	61 27%	162889 3%	233928 0%	296019 5%	919008 7%	8;15
$I_{\frac{3}{200}; \frac{1}{100}; \frac{3}{200}; \frac{1}{100}; \frac{95}{100}}$	78	55	62 28%	167362 64%	286330 81%	296019 5%	701051 3%	4;15

Comparing these results with the previous ones, where Constraint (22) was not enforced, we observe that requiring all areas to be large did not significantly affect the individual objectives. Moreover, even increasing α_5 to 0.9 still produces a good solution, with only a modest increase in f_1 . The threshold appears at $\alpha_5 = 0.95$, where we observe a noticeable increase in f_2 and f_3 , accompanied by only a slight improvement in f_5 .

In contrast to Table 4, achieving full area connectivity was not possible even with $\alpha_5 = 0.95$. This is reasonable, since enforcing all areas to be large encourages the model to assign some disconnected stations to the same area. Consequently, achieving full connectivity would require setting α_5 to its maximum value while omitting all intra-area objectives. However, even this may not guarantee full connectivity because of the domain reduction constraints added to the MIP (see Constraints 18, 19, 20, and 21).

5.7 Reducing the Number of Areas

In this set of experiments, we reduce the number of areas used in the model. Instead of partitioning the stations into 15 areas, we decrease this number to 13 and 11. This change requires recomputing the corresponding $f_k^{\min}$ and $f_k^{\max}$ values, making comparisons with the previously computed bounds no longer meaningful. The purpose of these experiments is to investigate whether using fewer areas leads to improvements in the individual objective components. Therefore, rather than comparing normalized objective values, we report the percentage change in each objective component relative to the corresponding instances in Table 5, as shown in Tables 6 and 7.

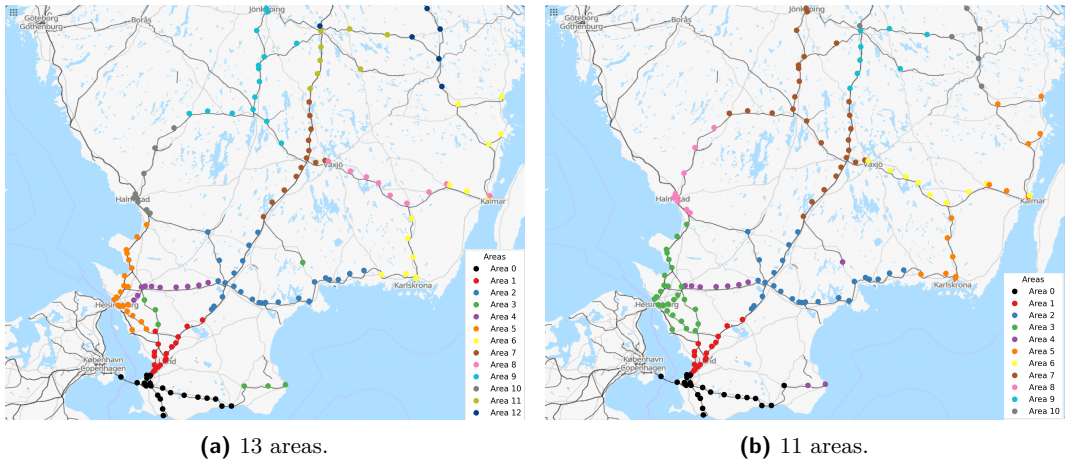
Reducing the number of areas to 13 had a negligible impact on the intra-area objectives, except when α_5 was increased to 0.95. Moreover, the connectivity measure improved remarkably in almost all instances, and the number of disconnected areas decreased to only three in the last instance. The objective f_5 improved in all instances, as expected, since having fewer areas reduces the total number of movements between them. These experiments

■ **Table 6** Results for 13 areas including a percentage comparison with the objective values of the corresponding instances from Table 5. Percentage increases are emphasized in bold text.

instance	r (m)	obj 10^{-3}	f_1 (track)	f_2 (st/end)	f_3 (mov)	f_4 (m^f/m^p)	f_5 (inter-flow)	#D;L areas
$I_{\frac{24}{100}; \frac{1}{100}; \frac{24}{100}; \frac{1}{100}; \frac{50}{100}}$	20	47	35 0%	157750 -3%	233640 0%	296445 0%	879591 -12%	5;13
$I_{\frac{19}{100}; \frac{1}{100}; \frac{19}{100}; \frac{1}{100}; \frac{60}{100}}$	31	49	35 0%	157750 -3%	233640 0%	296445 0%	879591 -12%	5;13
$I_{\frac{14}{100}; \frac{1}{100}; \frac{14}{100}; \frac{1}{100}; \frac{70}{100}}$	28	52	35 0%	157750 -3%	233640 0%	296445 0%	879590 -12%	5;13
$I_{\frac{9}{100}; \frac{1}{100}; \frac{9}{100}; \frac{1}{100}; \frac{80}{100}}$	33	54	35 0%	157750 -3%	233640 0%	296445 0%	879590 -12%	5;13
$I_{\frac{4}{100}; \frac{1}{100}; \frac{4}{100}; \frac{1}{100}; \frac{90}{100}}$	183	54	61 0%	157750 -3%	233640 0%	296019 0%	802831 -13%	4;13
$I_{\frac{3}{200}; \frac{1}{100}; \frac{3}{200}; \frac{1}{100}; \frac{95}{100}}$	22	38	143 130%	165950 -1%	282034 -1%	412464 39%	550718 -21%	3;13

show that reducing the number of areas generally improved connectivity and inter-area flow without a remarkable loss in the intra-area objectives. In Figure 4a, we illustrate the resulting partition for Instance $I_{\frac{3}{200}; \frac{1}{100}; \frac{3}{200}; \frac{1}{100}; \frac{95}{100}}$, where we achieve the highest connectivity without sacrificing the intra-area objectives.

Reducing the number of areas to 11 improved, as also observed with 13 areas, the objective component f_5 and the connectivity measure. In contrast, the objective component f_1 increased in most instances. A plausible explanation is that having fewer areas forces the model to assign more stations per area. In combination with the constraint prohibiting small areas, this likely results in areas with a higher deviation in the number of tracks from the maximum ℓ_1^{max} , which is captured by the objective component f_5 . In Figure 4b, we illustrate the resulting partition for Instance $I_{\frac{3}{200}; \frac{1}{100}; \frac{3}{200}; \frac{1}{100}; \frac{95}{100}}$, using 11 areas.



■ **Figure 4** Resulting partitions for Instance $I_{\frac{3}{200}; \frac{1}{100}; \frac{3}{200}; \frac{1}{100}; \frac{95}{100}}$.

■ **Table 7** Results for 11 areas including a percentage comparison with the objective values of the corresponding instances from Table 5. Percentage increase are emphasized in bold text.

instance	r (m)	obj 10^{-3}	f_1 (track)	f_2 (st/end)	f_3 (mov)	f_4 (m^f/m^p)	f_5 (inter-flow)	#D;L areas
$I_{\frac{24}{100}; \frac{1}{100}; \frac{24}{100}; \frac{1}{100}; \frac{50}{100}}$	5	49	47 32%	157750 -3%	233640 0%	328151 10%	842493 -15%	5;11
$I_{\frac{19}{100}; \frac{1}{100}; \frac{19}{100}; \frac{1}{100}; \frac{60}{100}}$	6	51	47 32%	157750 -3%	233640 0%	319490 8%	853193 -15%	5;11
$I_{\frac{14}{100}; \frac{1}{100}; \frac{14}{100}; \frac{1}{100}; \frac{70}{100}}$	6	51	48 37%	157750 -3%	233640 0%	323361 5%	833488 -17%	4;11
$I_{\frac{9}{100}; \frac{1}{100}; \frac{9}{100}; \frac{1}{100}; \frac{80}{100}}$	6	50	55 57%	157750 -3%	233640 0%	265753 -10%	781092 -22%	4;11
$I_{\frac{4}{100}; \frac{1}{100}; \frac{4}{100}; \frac{1}{100}; \frac{90}{100}}$	3	46	59 -3%	157750 -3%	233640 0%	290021 -2%	766461 -17%	4;11
$I_{\frac{3}{200}; \frac{1}{100}; \frac{3}{200}; \frac{1}{100}; \frac{95}{100}}$	3	38	69 11%	165708 -1%	277652 -3%	366409 24%	625022 -11%	3;11

6 Conclusions and Future Work

In this paper, we presented a MIP, formulated as a multi-objective optimization problem, for partitioning railway stations into a predefined number of dispatching areas for railway dispatching centers. The proposed approach jointly considers two key aspects of operational performance: the coordination effort required between neighboring dispatching areas, represented by inter-area interaction complexity, and the workload within each dispatching area, represented by intra-area operational complexity. By integrating infrastructure characteristics and traffic-related factors into a unified optimization framework, we provide a systematic and quantitative methodology for designing balanced dispatching areas.

We applied the proposed model to instances from the Malmö dispatching center in the southern Swedish railway network, demonstrating its applicability to realistic railway operations. The results reveal a trade-off between the intra-area objectives, which promote a more balanced workload within areas, and the inter-area objective, which promotes lower coordination effort and greater connectivity between areas.

Since our MIP includes multiple objective components, selecting appropriate weights is crucial. Determining these weights is typically the responsibility of network managers, as they reflect the relative importance of each objective. However, in our experiments, we evaluated a range of weight combinations to identify the most representative ones. This analysis can support decision-makers by providing guidance on how different weight settings affect the solutions, making it easier to prioritize among the competing objectives.

Other factors that may affect solution quality are the area size and the number of areas. In several instances, we showed that requiring all areas to be large had no noticeable impact on the different objective components. Furthermore, a moderate reduction in the number of areas improved inter-area measures and area connectivity without adversely affecting the intra-area objectives.

A key contribution of this work is showing that an exact method solves the sectorization problem within 1% of optimality, with all experiments completed in under 360 minutes. In contrast, Zhao et al. [18] aggregate intra-area workload into a single value and minimize deviations from its average, considering only one objective and obtaining heuristic solutions

in under 33 minutes (though this comparison should be interpreted with caution, as computation times are hardware-dependent and were not measured on the same machine). When considering a single objective, our exact method obtains optimal solutions in at most 23 seconds (see Table 2).

In this paper, we showed that optimization-based sectorization can support redesigning dispatching areas by explicitly balancing the trade-off between minimizing coordination across boundaries and maintaining manageable operational complexity within each area. Furthermore, robustness analysis under different traffic compositions and demand levels indicates the framework remains applicable under varying conditions, making it a promising decision-support tool for dispatching area planning.

For future work, several extensions to the proposed framework are possible. In this study, the number of areas is fixed. Allowing the model to decide the number of areas would make it more flexible by jointly optimizing both structure and size. However, this would increase computational complexity and may require decomposition methods or heuristics.

Moreover, since weighted-sum scalarization identifies only supported Pareto-optimal solutions, future work could apply alternative methods – such as the ϵ -constraint method – to characterize the complete Pareto front, including unsupported solutions, offering decision-makers a more comprehensive view of trade-offs between intra- and inter-area objectives.

Finally, applying the method to large national networks (e.g., the Swedish network) is computationally challenging. Aggregation or hierarchical models – merging low-importance stations into larger nodes – may help, while the main network structure is preserved.

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