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Towards autonomous goal-oriented self-organisation in railways

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ABSTRACT

Self-organisation, a concept with wide-ranging applications across disciplines, offers significant potential for advancing railway traffic management. This review synthesises existing definitions, identifies critical gaps, and evaluates the applicability of self-organisation principles to railway traffic management. It also introduces a classification of self-organising systems and emphasises the importance of autonomy and goal orientation for enhancing scalability, robustness, and adaptability in railway operations. Building on insights from common-pool resource management, we propose the concept of autonomous goal-oriented self-organisation, a novel framework that combines decentralised decision-making with dynamic rule adaptation to address the complexities of modern railway systems. Key contributions include a critical synthesis of existing definitions, a novel classification of self-organising systems emphasising autonomy and goal orientation, and a discussion of its implications for railway traffic management. The review bridges disciplinary perspectives to provide a cohesive understanding of self-organisation and proposes a research agenda that prioritises simulation-based validation, interdisciplinary approaches, and adaptive mechanism development. By offering actionable insights and theoretical advancements, the framework has the potential to inspire innovative, equitable, and sustainable solutions for railway traffic management and beyond.

1. Introduction

In the complex world of railway traffic management, ensuring efficient and reliable operations is a constant challenge. Disruptions, such as delays and unforeseen events, can significantly impact the smooth flow of traffic, leading to cascading delays and decreased service quality. Rescheduling is the real-time process of adjusting train timetables, namely updating the train path plans, in such a way that conflicts, due to disturbances as well as predicted secondary delays are avoided. Rescheduling, in case of disturbances, consists mainly of 3 types of measures: retiming when the arrival or departure times of a

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train at a given station are altered, reordering when the passing order of trains at a given station or junction is altered, and rerouting when a train detours over a different route. Real Time Traffic Plan (RTTP) incorporate the set of rescheduling actions for a given time horizon when a disturbance emerges (Quaglietta et al., 2016). RTTPs are currently monitored and updated in real-time by human dispatchers based on their own experience. However, the rescheduling problem is not trivial since the objective criteria of rescheduling are dynamic, depending on the cause, the magnitude, the propagation effect of the disturbance, and the priority (in terms of time, financial results, strategic objectives) of the service or line. In addition, the rescheduling problem is a large-scale combinatorial problem with a short available time of reaction by the dispatchers who in addition have partial information about the state of the problem (among others, passenger load of trains and/or station platforms, cost of delayed or cancelled train service, position accuracy of the train).

Currently, rail traffic management is performed centrally by traffic controllers (also called dispatchers) who take rescheduling decisions for all trains that are operating within a certain geographical region. For large and/or high-density rail traffic networks, a centralised traffic management problem can hence assume a large decisional and/or computational complexity. Automatic Decision Support Systems have hence been developed to support dispatchers in identifying effective rail traffic rescheduling strategies even in case of large/complex centralised traffic management problems. However, opposite to centralised traffic management, the concept of decentralised rail traffic rescheduling has gained popularity to reduce computational / decisional complexity and improving adaptability of centralised decision to local traffic conditions (Marcelli & Pellegrini, 2021).

A decentralised rail traffic management can indeed provide advantages in reducing the complexity of the train rescheduling problem from a large network or an area with dense traffic intensity, down to a smaller local area, thereby improving efficiency in computing and implementing dispatching strategies. That can hence lead to effective scalability of rescheduling algorithms and a more flexible traffic management which can more easily be adapted to local traffic conditions.

The research in this paper attempts to align the current understanding of self-organisation and propose a classification of self-organisation which includes introducing and defining a previously unexplored class. In addition, a research agenda is proposed to support a shared and consistent research direction across the scientific and industrial communities with a focus on the railway sector. To this end a comprehensive literature review is performed which starts from the origin of the self-organisation concept, highlighting the abundance of definitions for self-organisation across different disciplines, which leads to a lack of clarity and consensus on its meaning. Especially in the railway context, previous works propose either general definitions of self-organisation or focus on different aspects of the self-organisation of railway traffic management, namely decentralised decision making, communication or learning approaches (D'Amato et al., 2024; Marcelli & Pellegrini, 2021).

Furthermore, an aspect that previous self-organisation studies have not adequately addressed is the autonomy of self-organisation. In this context, the term "autonomy" is used in its literal sense, derived from the Greek "autos" (self) and "nomos" (rule, law) which means the ability of an entity to form and amend its own rules. The existing literature primarily focuses on self-organising systems that rely on static predefined rules or

systems where rules change through a passive process, i.e. the changes occur without active intervention from the system components themselves. There is limited research on systems where the agents actively formulate and update their own rules with the intention to achieve specific goals. In this respect, this paper aims to propose a framework for implementing autonomy within systems, including railways.

Outlined below are the primary contributions of this paper, highlighting the novel insights and advancements achieved in the domain of railway traffic management through the proposed dynamic self-organisation framework. These contributions are:

- A review of existing definitions of self-organisation across various disciplines and identification of current literature gaps in a shared, consistent definition of self-organisation in the railway sector.
- A classification of the self-organisation aspects found in literature based on the rule formation process
- Formulation of a novel, comprehensive definition for autonomous goal-oriented self-organisation, tailored to the railway domain based on conceptual and theoretical aspects shared across multiple disciplines.
- A modelling approach for self-organising rail traffic, drawing inspiration from common-pool resource management principles.
- A research agenda to further investigate the potential of autonomous goal-oriented self-organisation in railway operations.

The rest of the paper is organised as follows. Section 2 describes the organisation of complex systems focusing on structure. Section 4 presents self-organisation approaches in ground transportation (roadways and railways). Section 3 describes what concepts of self-organisation have been identified in the literature, and Section 6 provides a definition of autonomous goal-oriented self-organisation (AGOSO). Section 7 suggests a future research agenda for the development of self-organisation, and Section 8 concludes the paper.

2. Organisational structure of complex systems

Organising a system can be viewed as the problem of determining the optimal set and sequence of actions needed to be implemented by the system's components when they interact so that the system exhibits a desired behaviour. Different organisational structures provide different behaviour and consequently efficiency levels of a system. The main structures are the following:

- Centralised systems (Figure 1, centralised) in which there is only one central controller agent that directs all the inputs of each component of the system, maximising a single optimisation problem. In large-scale systems, this structure becomes unsuitable since it demands high computational resources as well as communication overhead, prohibiting scalability and robustness.
- Decentralised systems (Figure 1, decentralised), which divide the system into smaller centralised clusters of system components. This approach overcomes the limitation previously described in centralised systems allowing the controllers to handle lower
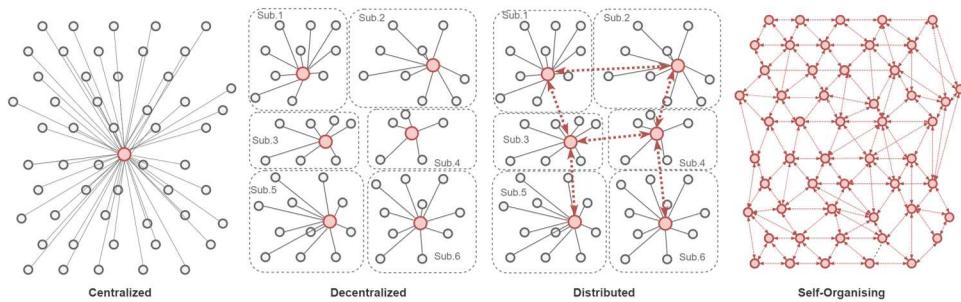
Figure 1. Graphical representation of (i) centralised, (ii) decentralised, (iii) Distributed, and (iv) Self-organising System.

computational load and storage requirements. However, the subsystems are not independent in a single system leading to conflicting actions between them resulting in suboptimal solutions.

- Distributed systems (Figure 1, Distributed) which have a similar structure to decentralised ones, however, the controllers of subsystems are allowed to exchange information regarding constraints or variables. Coordination among controllers allows the system to achieve better results compared to decentralised.
- Hierarchical systems (Figure 2), which have a different way of resolving conflicts between subsystems. In this approach, additional higher-level controllers serve multiple objectives and the overall computational efficiency of the system is improved.
- Combinations of the above.

However, nature follows a different approach to organising systems. In the case of self-organised systems (Figure 1, Self-organised), each element of the system possesses its own controller enabling it to perceive its immediate environment and interact with neighbouring elements. There are no higher hierarchical management levels. The elements follow a specific set of rules that control their actions depending on their local state. They interact either in a passive mode, just by observing the existence or actions of the neighbouring elements, or in an active mode, by exchanging messages, which allows them to cooperate and negotiate.

Based on the literature, we can observe that most approaches include the same set of elements identified in self-organising systems. Any self-organising system consists of a set of entities that interact. The compound of interactions results in the system's emergent behaviour that is either beneficial, neutral or non-beneficial. However, there is no deterministic inference between interactions and behaviour, at least in more complex systems. Entities' interactions follow a set of rules that are applied either globally or locally depending on the local state.

Serugendo et al. (2013) classify self-organising systems into three primary groups, based on the underlying laws that guide self-organisation. The authors suggest 3 classes: Natural systems, Business and Economics systems, and Artificial systems. In the first class, Natural systems, the laws that guide self-organisation are dictated by nature, and they can be further classified into (i) Physical systems, when the laws are in the
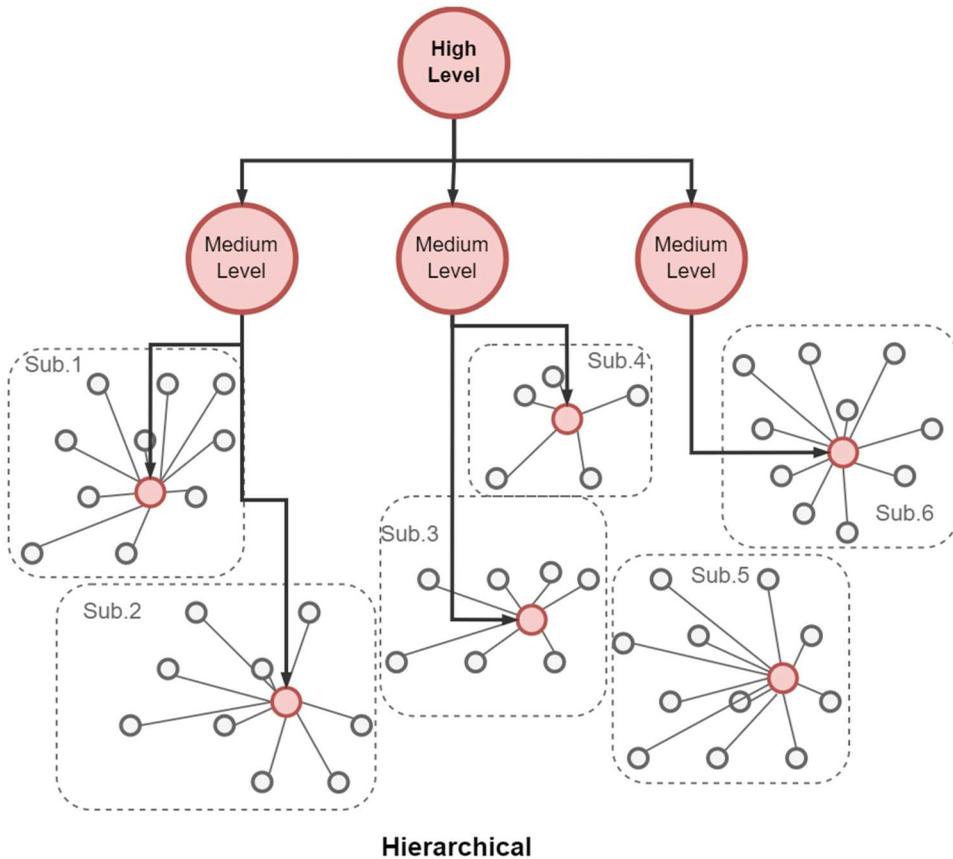
Hierarchical

Figure 2. Hierarchical system.

context of physics and chemistry, (ii) Biological systems and (iii) Social systems in which entities exhibit social behaviours that lead to self-organisation. In contrast to Natural systems, Business and Economics are driven by market forces and profit maximisation, where models and strategies are employed to manage system dynamics. Finally, artificial systems are human-designed constructs explicitly engineered to exhibit self-organising characteristics.

3. Concept of Self-Organisation

3.1. Core components of Self-Organisation

Self-Organisation is a process in which local component of a system interact in such a way that global structure or behaviour emerges without central coordination. Across the literature, several fundamental components are consistently identified:

- **Autonomy**: Agents operate independently based on local information, without a centralised decision-maker. This principle is fundamental to distributed systems in cybernetics (Ashby, 1947) and has been applied to wireless and transportation networks

(Prehofer & Bettstetter, 2005). In railway traffic management, this autonomy allows trains to act based on their own objectives and the local traffic state.

- **Emergence**: The system exhibits macroscopic behaviour that is not explicitly programmed but arises from agent interactions. This has been demonstrated in natural systems (Camazine et al., 2001), logistics (Bartholdi, 2009), and urban traffic (Gershenson, 2005), where simple rules lead to coordinated global outcomes. Emergence in railways could include conflict-free rescheduling or headway harmonisation.
- **Adaptability**: Self-organising systems adapt to changes in their environment or internal state, either through learning or dynamic rule adjustment. Adaptability is a hallmark of robust systems and has been emphasised in engineered contexts by Gershenson and Heylighen (2003), and in distributed traffic management by Gershenson (2020).
- **Feedback**: Agents receive and act upon feedback about the system's performance, enabling iterative improvement and self-regulation. This is critical for creating closed-loop interactions where agent behaviour evolves over time. Feedback loops are well established in control theory and in self-organising systems literature (De Wolf & Holvoet, 2005; Heylighen, 2002).
- **Scalability**: A system must remain efficient as its size or complexity increases. Self-organising architectures often outperform centralised approaches in scalability, especially in mobile ad hoc networks and transport systems (Gershenson, 2020; Prehofer & Bettstetter, 2005). In railways, scalability is essential for managing dense traffic without centralised bottlenecks.

These components form the conceptual basis for evaluating railway traffic control strategies in this review and underlie the development of the proposed AGOSO framework. As the following sections will show, current railway systems may embody some of these features (e.g. autonomy or local feedback), but rarely integrate them all in a coherent, goal-oriented manner.

The abundance of definitions found in the literature for self-organisation underlines the complexity of describing the components and processes of a system that self-organises. These definitions come from different disciplines like thermodynamics, biology, information theory, social sciences, transportation and others. Collecting their common elements and comparing their differences, we can reach a conclusion on what are the fundamental parts of self-organisation and what processes are followed by such systems.

3.2. Emergence and system coherence

Emergence refers to the development of global patterns or behaviours resulting from local interactions. In self-organising railway systems, this may involve spontaneous conflict resolution, synchrony in dispatching, or headway equalisation, achieved without central scheduling.

Ashby (1947) introduced the idea that a well-organised system minimises instability by adjusting internal relations in response to its own state. In cybernetics, this principle of "good organisation" is measured by the system's ability to converge toward a stable equilibrium. More recently, in transportation systems, emergent behaviour has been observed

in systems of adaptive traffic lights (Gershenson, 2005) and metro operations (Gershenson, 2011), where agents coordinate indirectly through shared state signals or thresholds.

In railways, emergent order is particularly valuable when responding to unplanned disruptions, where precomputed optimisation plans break down, and real-time local coordination becomes necessary.

3.3. Intentionality and rule adaptation

While self-organisation in physical or biological systems is typically spontaneous and unguided, self-organisation in engineered systems, such as railways, must be intentional. Agents are expected to pursue system-level objectives such as minimising delay, resolving disturbances, or improving energy efficiency. This introduces a controlling layer into the system's behaviour: not all emergent patterns are acceptable but only those aligned with specific goals.

Pitt (2021) and Ostrom (1990) offer valuable conceptual models for intentional self-organisation. Pitt emphasises the role of self-awareness and reflection: agents must be capable of observing their environment, evaluating their performance, and adapting accordingly. Ostrom introduces the idea of nested rule structures:

- Operational rules govern everyday interactions,
- Collective-choice rules determine how operational rules are modified,
- Constitutional rules define who is allowed to make these changes.

These nested structures (Figure 3) provide a useful model for building adaptive traffic control mechanisms in railway networks, where train agents might adapt dispatching rules, propose new priorities, or negotiate goal trade-offs dynamically.
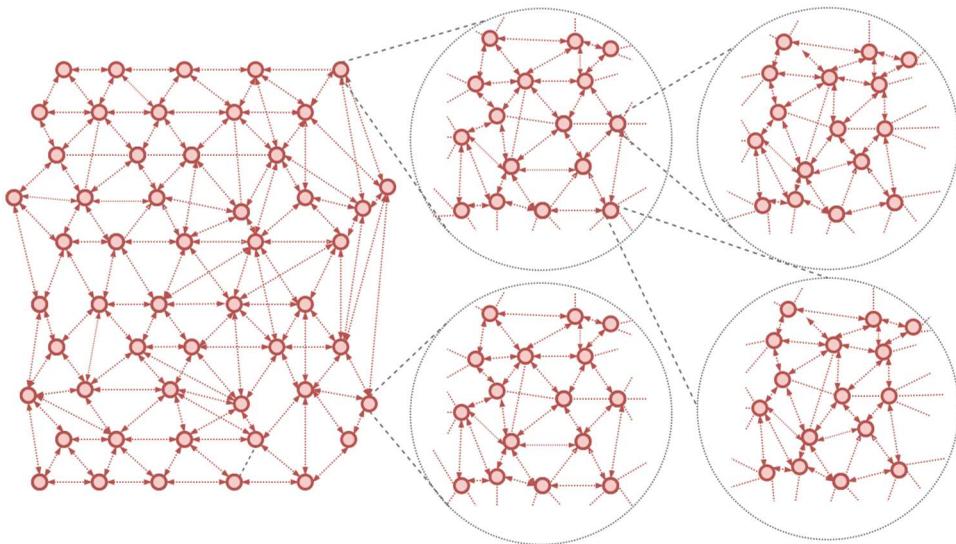

Figure 3. Structural nesting levels of self-organisation.

The principles outlined in this section are translated into domain-specific logic in Section 6, where we apply them to the development of the AGOSO framework for railway traffic management.

In this paper, we distinguish between the process and the system. Self-organisation refers to the process by which global patterns and coordination emerge from local interactions without central control. A self-organising system, in contrast, is a system that undergoes such a process, exhibiting emergent order and adaptability. In engineered settings such as railway traffic management, self-organisation is often intentional: agents apply local rules and feedback to achieve explicit system-level objectives (e.g. minimising secondary delay). This distinction ensures conceptual clarity throughout the paper.

4. Self-Organisation in ground transportation

4.1. Self-Organisation in road transport

Self-organisation, defined as the ability of a system to function without a central node, has long been observed in road traffic. Historical evidence shows that cart drivers in Pompeii drove consistently on the right side when meeting on two-lane streets (Poehler, 2017). Modern examples include uncontrolled intersections, where right-of-way is resolved locally: in most right-hand traffic countries, priority is given to vehicles from the right, while in the USA, the first to arrive at an intersection proceeds (California Department of Motor Vehicles, 2009). Similarly, roundabouts and lane changing require drivers to adapt speed and yielding behaviour to perceived conditions, creating self-organised order without explicit signals.

Research translates these behaviours into three major approaches (Li et al., 2023):

Self-adaptive infrastructure. Traffic lights or signs adapt to observed flow or exchange information. Gershenson (2005) proposed self-organising traffic lights that remain red until vehicle thresholds are reached, while Cesme and Furth (2014) introduced local actuated rules for coordination such as secondary extensions (serving approaching platoons) and dynamic synchronisation between closely spaced signals.

Vehicle-based organisation. Vehicles self-regulate individually or collectively, often via Vehicle-to-Vehicle (V2V) communication. Fernandes and Nunes (2010) demonstrated platooning that minimises spacing and increases capacity, initially under externally controlled leaders. Jin et al. (2013) extended this with autonomous leader assignment and Vehicle-to-Infrastructure (V2I) reservation requests at intersections. Even partial penetration improves performance: Goldental and Kanter (2020) showed that a small fraction of automated vehicles can stabilise freeway flow without explicit V2V communication.

Cooperation between vehicles and signals. Hybrid approaches combine Connected Adaptive Cruise Control (CACC) with infrastructure signals. H. Liu et al. (2019) proposed algorithms granting dedicated green phases to detected platoons of CACC vehicles, achieving a 30% speed increase and fuel improvements even at 40% penetration. Similarly, Kaiwen Zhang and Ma (2024) apply reinforcement learning to optimise signal control with connected vehicles.

Across these applications, the central insight is that local negotiation, feedback adaptation, and distributed intelligence can generate robust traffic coordination. While railways face stricter safety and infrastructure constraints, the principles demonstrated in

road systems, adaptive rules, agent communication, and feedback loops, offer valuable lessons for developing self-organised railway traffic management. The following section explores how similar principles have been adapted to railway traffic management, under stricter infrastructure and safety constraints.

4.2. Self-organisation in railways

4.2.1. Centralised railway traffic management

Research on centralised real-time railway traffic management (rtRTMP) has advanced rapidly, producing sophisticated models and algorithms to support dispatcher decision-making during disturbances. Centralised frameworks typically rely on mathematical programming (e.g. MILP formulations), decomposition methods, and metaheuristics, often integrating rolling-stock and passenger objectives.

A recent review by Zhan et al. (2024) highlights the growing emphasis on uncertainty-aware models, where stochastic delays and demand fluctuations are explicitly represented. Passenger-oriented approaches are also gaining prominence, with Sharma et al. (2023) surveying models that minimise passenger travel time and missed connections alongside operational efficiency.

Methodological advances include efficient MILP integrating decomposition for large-scale optimisation (Lövétei et al., 2025), predictive optimisation integrating data-driven delay forecasts (Pascariu et al., 2025), and integrated speed management under power constraints (Xiu et al., 2025). Centralised frameworks have also been applied to severe disruption recovery (Zhang et al., 2023), with some integrating rolling stock and crew scheduling into timetable rescheduling (Yin et al., 2025).

Together, these studies form the state of practice in centralised rail traffic management. While highly effective in certain contexts, their reliance on global optimisation and central coordination contrasts with the distributed, adaptive focus of self-organising approaches reviewed in the following section.

4.2.2. Decentralised railway systems

Self-organisation in railway systems has emerged as a promising strategy to address the scalability, adaptability, and computational complexity challenges inherent in centralised traffic management. While explicit references to "self-organisation" are still limited in the railway literature, a growing body of work demonstrates characteristics such as local autonomy, decentralised coordination, adaptive rule formation, and negotiation-based decision-making, key features of self-organising systems.

Perrachon et al. (2020) propose a decentralised multi-agent architecture where trains locally exchange utility values and resolve conflicts by prioritising the train that minimises weighted secondary delays. Fay (2000) introduces a market-based negotiation model in which train agents interact with track segment agents to dynamically allocate routes. J. Liu et al. (2018) design a peer-to-peer train dispatching mechanism, where junction agents apply genetic algorithms to resolve sequencing conflicts. This is extended by J. Liu et al. (2019), who develop negotiation-based dispatching strategies for bottleneck management using local train-level coordination. Kuperberg et al. (2020) explore a blockchain-based infrastructure where smart contracts enable autonomous interaction among trains and infrastructure components, offering a secure and decentralised control mechanism.

Recent research has pushed these ideas further. D'Amato et al. (2024) propose a modular, neighbourhood-based coordination strategy in which trains autonomously identify conflict zones, propose resolution strategies, and negotiate local consensus, thus demonstrating full self-organisation at the operational level. Bretas et al. (2021) employ decentralised reinforcement learning through a DEC-POMDP framework, enabling agents to learn policies that reduce dwell time and avoid deadlocks. van Lieshout et al. (2022) simulate a no-timetable dispatching scenario where crew and rolling stock are managed by local rules under decentralised control logic.

Several works also leverage reinforcement learning to further embed self-organising behaviour. Khadilkar (2019) presents a scalable RL-based approach for bidirectional line scheduling, where agents make real-time decisions based on Q-values derived from local state-action desirability. Ying et al. (2024) develop a multi-agent deep RL framework to manage disruptions using adaptive short-turning of services. Yue et al. (2024) introduce a scalable train timetable rescheduling approach using graph-structured RL agents to encode local network topology and dynamics. Schneider et al. (2024) demonstrate a real-world application of multi-agent deep reinforcement learning for intelligent traffic and capacity management in railway networks, enabling trains to make real-time decisions under varying operational scenarios.

To consolidate these contributions, Table 1 maps the reviewed literature to key aspects of self-organisation. This structured view highlights the progressive shift in the field toward dynamic, decentralised, and train-centric control paradigms, laying the

Table 1. Mapping of railway challenges to self-organisation aspects, mechanisms, and representative studies.

| Self-organisation Aspect	Railway Challenge	Example Mechanism	Representative Study
Goal Orientation	Punctuality	Dynamic prioritisation	D'Amato et al. (2024)
	Train conflict resolution	Train neighbourhood formation and local consensus	
	Real-time disruption recovery	Multi-agent RL-based short-turning and rescheduling	Ying et al. (2024)
Rule Negotiation & decentralisation	Capacity Bottlenecks	Local rerouting decisions	H. Liu et al. (2019)
	Bottleneck dispatching	Agent negotiation for train order	
	Scalability in traffic rescheduling	Graph-based RL agents for large-scale coordination	Yue et al. (2024)
	Decentralised bottleneck dispatching	Smart contracts and train-infrastructure negotiation	Kuperberg et al. (2020)
Local Adaptation & Feedback Loops	Energy Optimisation	Adaptive speed control	Khadilkar (2019)
	Deadlock and dwell time reduction	RL via DEC-POMDPs	Bretas et al. (2021)
Nested Rule Adaptation	Delay Propagation Control	Platform allocation, reordering	J. Liu et al. (2018)
	Train sequencing at junctions	P2P negotiation with genetic algorithm	
Distributed Control & Coordination	Crew and Rolling Stock Usage	decentralised dispatching	van Lieshout et al. (2022)
	Disruption recovery	Short-turning via multi-agent RL	Ying et al. (2024)
	Large-scale capacity and flow management	Multi-agent DRL to manage network-level coordination	Schneider et al. (2024)
	No-timetable dispatching	Rolling stock and crew managed by decentralised agent rules	van Lieshout et al. (2022)
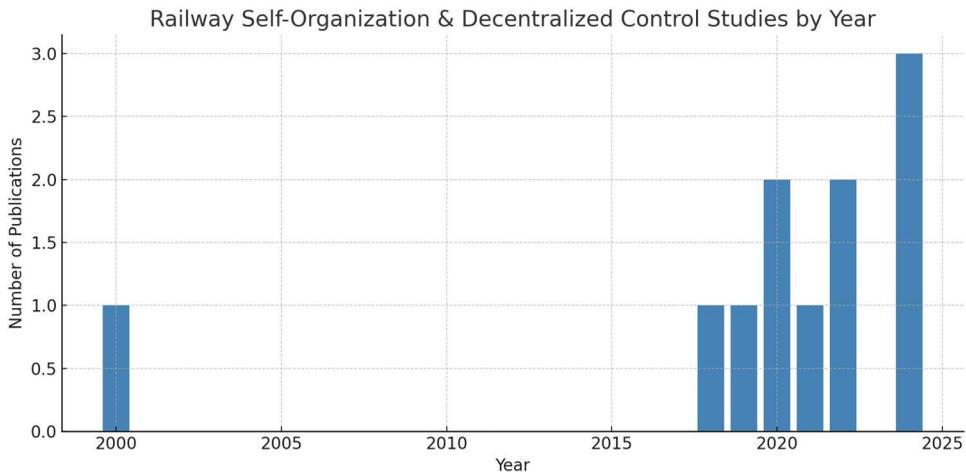
Figure 4. Railway self-organisation and decentralised control studies by year.

foundation for the Autonomous Goal-Oriented Self-organisation (AGOSO) framework introduced in this paper.

Over the past two decades, a growing body of work has investigated decentralised and self-organising principles applied to railway traffic management. While early studies were isolated and mostly conceptual, recent years have seen a noticeable increase in publications proposing agent-based, learning-driven, and modular coordination frameworks.

Figure 4 illustrates the timeline of key railway-related studies that contribute to this emerging field. The increase in activity since 2020 reflects a growing interest in applying self-organisation principles to real-world operational problems, supported by the availability of simulation environments, data, and machine learning tools.

It is also useful to compare self-organisation in railways with that in road transport, as both domains involve distributed agent behaviour but under differing operational constraints. In road systems, self-organisation arises from spontaneous behaviour of human drivers or connected vehicles, operating with soft constraints and significant freedom. Conversely, rail systems operate on rigid infrastructure with safety-critical requirements, requiring structured, rule-driven coordination. However, concepts such as adaptive negotiation, platooning, and decentralised signal control in roads provide valuable inspiration for modelling train-level interactions, provided these are adapted to rail's operational and regulatory constraints. Especially, by leveraging advances in agent-based modelling, local learning, and negotiation protocols, railway operations are increasingly capable of embedding self-organising properties at scale. These developments align with the vision of AGOSO, shifting from static, centrally prescribed control to systems where agents define and adapt their own rules to meet performance objectives under real-world uncertainty.

4.3. From decentralisation to self-organisation in railways

While decentralisation has been widely explored in railway traffic management, it does not inherently imply self-organisation. Decentralised systems typically grant local autonomy to

subsystems but continue to operate under fixed rules and externally imposed objectives. Peer-to-peer coordination is often limited or hierarchical, and system-wide coherence is ensured through top-down delegation rather than local interaction.

In contrast, self-organising systems, as defined in this study, require not only local autonomy but also the capacity for agents to adapt their behaviour through feedback, negotiate evolving rules, and pursue system-level goals from within. Such systems exhibit emergent behaviour arising from local decisions, rather than from centrally planned optimisation. While existing studies, such as those by J. Liu et al. (2018, 2019), van Lieshout et al. (2022), and Bretas et al. (2021), partially exhibit these properties, they often lack one or more of the key components: dynamic rule evolution, embedded goal-orientation, and emergent system-wide coordination.

This observation motivates the development of the Autonomous Goal-Oriented Self-Organisation (AGOSO) framework, which builds on existing decentralised approaches but extends them with three critical components: (i) autonomy in rule formation and adaptation, (ii) goal-orientation embedded in agent behaviour, and (iii) emergent coordination without hierarchical control. AGOSO thus fills the conceptual and methodological gap between existing decentralised systems and truly self-organising railway traffic management.

5. Towards Goal-Oriented Self-Organisation: a classification framework

5.1. Rule-based classification of Self-Organisation

The classification of self-organising systems presented in this section is proposed by the authors. This classification represents one of the key contributions of this paper, as it operationalises self-organisation concepts for application in railway traffic management. It is not derived directly from existing taxonomies, although it is informed by established frameworks on self-organisation in complex systems (De Wolf & Holvoet, 2005; Heylighen, 2002; Serugendo et al., 2013). Earlier taxonomies typically distinguish between natural versus engineered systems, or spontaneous versus guided emergence. In contrast, our classification reframes the discussion by focussing on rule formation and adaptation as the key differentiating principle. Specifically, we ask:

- Who creates or modifies the rules.
- Under what conditions do rules adapt.
- How does this process influence coordination in railway traffic management.

By answering these questions, we define three categories of self-organising systems: Heteronomous, Semi-autonomous, and Autonomous Goal-Oriented Self-Organising (AGOSO) systems. This framework is designed to be operational, clarifying the role of rule-making in self-organisation and providing categories that can be directly applied to railway traffic management, where operational rules critically shape safety, efficiency, and adaptability.

The three classes, illustrated in Figure 5, are as follows:

- **Heteronomous self-organisation** refers to the systems in which the rules that its components follow are either pre-existing or imposed by an external entity. The former refers
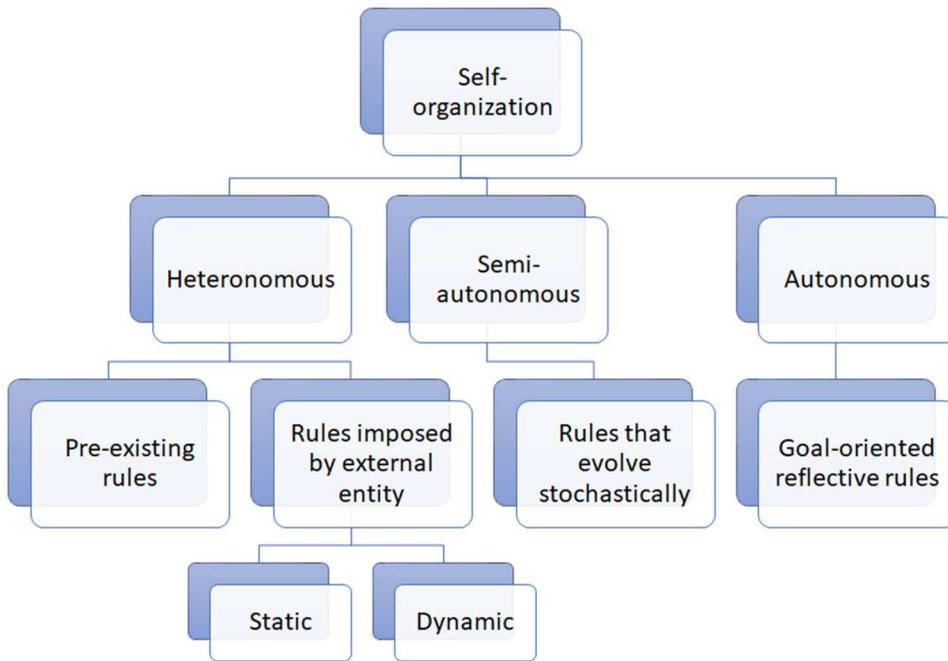
Figure 5. Classes of self-organisation.

to exogenous factors like environmental conditions or physical laws, whereas the latter includes all the systems that have to follow rules formulated by external entities and imposed on the system, like a government that wants to regulate a market, or a researcher who formulates rules at the design phase. In this category, rules can either be static and imposed once, or they can be dynamically updated by the external entity. In railways, Infrastructure Managers use internal dispatching manuals prescribing fixed train priority hierarchies (e.g. passenger trains over freight, or long-distance over regional). Agents (trains, stations) merely execute these rules without the ability to modify them.

- **Semi-autonomous** self-organisation refers to systems where the rules are being updated by inherent properties of the system and not an external entity. However, the update happens stochastically, without the control of the system's entities. An example in the railway setting could be the genetic algorithms or reinforcement learning methods that, during offline training, search for dispatching or rescheduling policies. The resulting rules are then deployed in operation, but agents themselves do not negotiate or create rules.

- **Autonomous self-organisation** refers to systems where the rules are established to achieve specific goals or outcomes, and they can be analysed and modified based on feedback and experience. An example in the railway traffic environment could be the following: at a congested junction, train agents exchange proposals for temporary priority rules ("give way to the train with the highest passenger-delay cost per minute"). A negotiation or voting mechanism selects the rule, and KPI feedback determines whether the rule persists or is revised.

Table 2. Operational comparison of the three classes of self-organisation, reframed for railway traffic management.

Class	Rule Authorship	Adaptation Trigger	Railway Example
Heteronomous	External authority (regulator, dispatcher)	Exogenous updates (rulebook revisions, timetable changes)	Fixed priority rules in internal dispatching manuals
Semi-autonomous	System-level mechanisms (evolutionary algorithms, offline optimisation)	Stochastic/endogenous changes discovered during simulation	GA-based search of rescheduling policies; offline learning of robust dispatch rules
Autonomous Goal-Oriented (AGOSO)	Local agents (trains, stations) propose and revise rules collectively	Real-time KPI feedback triggers negotiation or voting	Train agents negotiating temporary priority rules at a junction to minimise passenger delay

Notes: The novel AGOSO class highlights intentional, goal-driven rule formation.

The majority of applications of self-organisation found in the literature follow the Heteronomous self-organisation approach by formulating a set of rules before the system starts operating, aiming to optimise a metric on a small set of system states (Table 2). The semi-autonomous self-organisation with a stochastic update of the rules has also been applied by implementing genetic algorithms that optimise the policy of the entities based on the global efficiency of the system. However, to our knowledge, there is no Autonomous Goal-oriented Self-organisation approach with active updating of the rules in the literature.

Unlike heteronomous or semi-autonomous systems, AGOSO does not rely solely on externally imposed or stochastically generated rules. Instead, it enables agents to deliberately formulate, negotiate, and adopt rules in real time, with the explicit purpose of achieving agreed system-level goals. This introduces a dimension of intentionality into self-organisation that bridges local autonomy with collective objectives.

The novelty of AGOSO lies in this agent-driven governance of rules. Whereas semi-autonomous systems rely on stochastic or optimisation-based processes that produce rules externally and feed them back into the system, AGOSO internalises this process: the agents themselves actively create and revise their own rules. This shift transforms adaptation from being merely reactive and implicit into being deliberate, transparent, and purposeful, directly aligning local behaviour with collective railway objectives. For example, at a congested junction, train agents could exchange proposals for temporary priority rules (e.g. "give way to the train with the highest passenger-delay cost per minute"). A negotiation or voting process would determine the rule to be applied, while KPI monitoring decides whether it remains in force or is revised. In this way, AGOSO represents a step beyond adaptation by emergence, it introduces adaptive rule-making as an intentional process embedded within the agents themselves.

This classification provides a conceptual lens for situating different approaches to railway traffic management. Heteronomous systems capture today's reality of dispatcher-led, rulebook-driven operations. Semi-autonomous systems reflect the increasing use of optimisation and learning methods, where adaptation occurs but remains detached from agent-level decisions. AGOSO systems, in contrast, embody the vision of autonomous, self-organised railway management that this paper advances. By focussing on rule authorship and adaptation mechanisms, the framework connects directly to the proposed definition and approaches in rail traffic detailed in Section 6 and the research

agenda in Section 7, where we formalise railway traffic management as a Common-Pool Resource (CPR) problem governed through nested rule structures. This linkage ensures that the classification is not only conceptual but also directly actionable for structuring future research and system design.

6. Proposed definition and approaches for self-organisation in rail traffic

6.1. Railways as a common-pool resource problem

Ostrom (1990) has shown that self-organisation can solve CPR problems, when the decentralised entities of a system agree upon, follow and update a set of rules that define their actions. Similarly, if the railway traffic management problem can be modelled as a CPR, then it can also be solved, by allowing the entities of the system to formulate and update their own rules of action to achieve their intended goal.

We suggest that the railway traffic system can be modelled as a CPR appropriation problem. Wills-Johnson (2010) argues that because railway tracks are subtractable, when a slot is allocated to a stakeholder it is not available to others, and tracks are non-excludable since third-party access is mandated, at least in EU (Council of European Union, 2012), railway tracks constitute a CPR and they could potentially be governed as a CPR. Although Wills-Johnson is referring to governance by economic regulators, we argue that CPR governance can be extended to railway traffic management.

We model railway capacity as a Common-Pool Resource (CPR): track slots are subtractable and, under mandated access regimes, effectively non-excludable. Agents (trains, stations) pursue shared performance indices (delay, headway stability, passenger delay) under safety constraints enforced by a supervisory layer. AGOSO implements Ostrom-style nested rule governance: agents apply operational rules, can propose/vote to modify them (collective-choice), and are constrained by constitutional rules (who is allowed to change what), all under continuous KPI feedback. This formalises intentional self-organisation for rail.

6.2. Defining autonomous goal-oriented self-organisation

While self-organisation is frequently referenced in the literature, a precise definition has not been established due to its various emerging forms, and especially within the domain of railway systems. Based on the classification provided on (Figure 5) we seek to clarify the concept of autonomous goal-oriented self-organisation. The definition of autonomous goal-oriented self-organisation should include the following three aspects to better describe its holistic nature:

- **Autonomy**: The agents within the system can create or modify their own rules of action. This implies a dynamic and adaptable system where rules are not static but evolve based on the system's needs and goals.
- **Goal-oriented**: The ultimate aim of this self-organisation process is to achieve a specific, predetermined goal. This highlights the purposeful nature of the system, where actions are not random but directed towards a desired outcome.

- **Self-organisation**: The application of these self-formulated or updated rules leads to the emergence of a new system organisation. This suggests that the system is capable of restructuring itself to better achieve its goals.

Based on these components, which collectively describe a system that is not only self-organising but in addition, goal-oriented and autonomous. The system's agents have the mechanism to adapt their behaviour and its organisation to achieve desired outcomes. This holistic view of self-organisation is particularly relevant in the context of railway traffic management, where the ability to adapt and respond to dynamic conditions is crucial for efficient and reliable operations.

We argue that Autonomous Goal-Oriented Self-organisation is the dynamic process by which the agents of a system formulate or update their own rules of action such that, by adhering to them, a new system's organisation will emerge to intentionally accomplish a collective goal.

6.3. Modelling aspects in an autonomous goal-oriented self-organised rail traffic

Based on the given definition of autonomous goal-oriented self-organisation, the agents that participate in the rule-developing process and the available actions that these agents can implement are the first things that need to be defined. The agents can be trains, switches, interlocking areas, or even traffic controllers and consequently, this selection determines the set of their available actions. Furthermore, the available means of communication must be defined, which will specify how the interaction process between the agents will take place. Finally, the goal (or set of alternative goals) that the system is targeting, as well as the level of intelligence that the agents should acquire in order to predict if and how rules should be updated to provide the intended results.

Railways consist of a network of tracks on which trains, following a set of rules, can be allocated and operated on. Trains move in the network while interacting with each other and ensuring safe and efficient transport services and so they can be modelled as the entities of a system that self-organises. The self-organising rail traffic system can be homogeneous, namely, all trains are of the same type of priority and with similar if not identical technical characteristics, but it can also be heterogeneous, where a set of trains have a priority over another set of trains.

Traffic controllers are not considered self-organising agents in this model since they centralise the process of traffic management, need higher computational capacity, demand high communication overhead and their objective may not overlap with each train's objective. However, they are considered necessary since they have a supervisory role to ensure that traffic management decisions taken by the trains are always in line with safety and operational constraints.

The set of actions that trains can choose from to operate will include apart the common actions found in literature, namely choosing between stopping or running, retiming, reordering and short-turning the following:

- Adaptive speed control: trains can adjust their speed according to the local state of the network.

- Giving priority: trains can decide to give their priority to other trains.
- Skipping a stop: trains will have the ability to skip a stop if this reduces negative effects on traffic.
- Adding a stop: depending on the passenger load or flow at stations, trains can add stops in their route.
- Rerouting: trains may use alternative routes,
- Cancelling a path: trains can cancel their scheduled path.
- Cancelling part of a train path: On some occasions, trains can decide to cancel a part of their path.
- Extending path: depending on the situation of the traffic and service demand, trains can extend their route, adding a route part at the end or the beginning of their route.
- Adding a route: if service demand is high a train can take the initiative to implement a route although this was not scheduled beforehand.
- Mechanical coupling with another train: if is necessary then two trains can couple and travel together, minimising capacity demand.
- Virtual Coupling of trains: trains will have the ability to virtually couple reducing capacity demand.

The list of allowed actions that trains can implement is a subset of the list of available actions. The rules of the higher levels will determine what actions are available.

In terms of communication, trains can exchange operational messages for sharing traffic status information. For the self-organising process, they need to communicate for evaluating the result of the rules applied, the need of updating or introducing new rules, the suggestion of new rules and the voting for accepting new rules or not. This can be implemented continuously or at specific time points. A vocabulary for these inter-actions should be developed following the approach of Smith (1980).

Finally, the goal of railway traffic operation is to improve a set of performance indices, including schedule adherence, capacity consumption and passenger punctuality. In the proposed goal-oriented autonomous self-organisation rail traffic system, trains should share common performance indices as the objective (shared goal). However, if this is not achievable, due to external disturbances, then the objectives of each train can change depending on the situation. Especially in a system where stakeholders compete on the common resource (infrastructure capacity), a commonly beneficial outcome should also be a rule that is agreed upon by the system's entities. So the objectives of the system in disturbed scenarios are also a rule for the self-organising system to define. Thus, goal-oriented self-organisation of the railway traffic system can be defined as *the process by which trains develop and update their rules of deciding what actions should be implemented in order to reach or retain a performance index*.

6.4. Bridging review and research agenda

The preceding sections have demonstrated that, despite a growing body of work on decentralised and adaptive control in railways, a comprehensive and cohesive framework for self-organisation remains absent. Most studies fall short in integrating autonomy, goal-orientation, and adaptive rule mechanisms into a unified operational logic. This review has also revealed that while individual components of self-organisation are present

across various contributions, they are rarely coordinated toward emergent, goal-driven system behaviour.

To address this gap, the following research agenda does not propose an abstract or disconnected roadmap. Rather, it builds directly upon the conceptual shortcomings and operational limitations identified in the literature. The Autonomous Goal-Oriented Self-organisation (AGOSO) framework is therefore both a response to, as well as a synthesis of, the fragmented insights reviewed earlier. The agenda outlines concrete steps to implement and evaluate AGOSO, aiming to systematise local autonomy, embed goal-orientation at the agent level, and enable rule negotiation and adaptation through interaction. These steps are essential for transitioning from theoretical constructs to real-world, scalable applications in railway traffic management.

7. Research agenda

While the potential of autonomous goal-oriented self-organisation in railway systems has been acknowledged, current research lacks a comprehensive framework to guide its development and implementation. This research agenda is proposed to bridge the existing knowledge gap by listing steps to define the concepts of self-organisation, analyze its structure, model its functions and assess its impact on railway operations. Consequently, the agenda proposes a phased approach, beginning with defining the fundamental concepts and principles of autonomous goal-oriented self-organisation in the railway context. Subsequent steps involve developing mathematical models and computational simulations to analyze the behaviour of these systems, followed by real-world experiments and pilot studies to assess their impact on railway operations.

To achieve autonomous goal-oriented self-organisation in railway systems, this research agenda proposes four key steps as they are listed in Tables 3–6. For each step, a set of alternative approaches is proposed with their advantages (+) and disadvantages (-). The first step is to define clear objectives for the system, outlining desired outcomes. Next, it is necessary to investigate the nested nature of self-organisation, examining how this phenomenon operates at various levels within the railway context. Following this analysis, a Rule Negotiation and Adaptation mechanism should be developed and implemented, enabling the system to dynamically adjust its behaviour in response to changing conditions. Finally, it is important to assess different modelling approaches in

Table 3. Research agenda step i: definition of objectives.

Possible approaches	Advantages -- Disadvantages
Multi-Criteria Analysis	(+) Provides a structured framework for evaluating multiple objectives.
	(+) Allows for stakeholder participation in decision-making.
	(+) Can handle both quantitative and qualitative criteria.
	(−) Can be subjective due to the weighting of criteria.
	(−) Requires careful selection and definition of criteria which may not fully capture the complexity of interactions between them
Users studies and experiments	(+) Aligns with societal values incorporating user preferences
	(+) Improves passenger satisfaction
	(+) Enhances fairness and equity
	(−) Requires extensive data collection and analysis.
	(−) May be subjective and difficult to quantify.
	(−) Potential for conflicting objectives. and may not be representative of all user groups.

Table 4. Research agenda step II: nested self-organisation.

Possible approaches	Advantages -- Disadvantages
Multi-Agent Simulation	(+) Captures complex interactions between different levels of the railway system. (+) Allows for testing various coordination mechanisms. (−) Requires detailed modelling of agent behaviour and interactions. (−) May be computationally expensive for large-scale simulations.
Mathematical Modeling	(+) Allows for formal analysis and prediction of system behaviour under different conditions. (+) Can provide insights into the underlying mechanisms driving self-organisation. (−) Requires simplifying assumptions, which may not fully capture the complexity of real-world systems. (−) Model validity depends on the accuracy of assumptions and the ability to calibrate parameters.

Table 5. Research agenda step III: Rule negotiation and adaptation mechanisms.

Possible approaches	Advantages -- Disadvantages
Decentralised Decision-Making Framework	(+) Enables real-time adaptation of rules based on local information. (+) Promotes flexibility and responsiveness to changing conditions (−) Requires robust communication and coordination mechanisms. (−) May lead to conflicts between agents with competing goals.
Evolutionary Algorithms/ Genetic Programming	(+) Exploration of a vast solution space for potentially novel and effective rules. (+) Adaptability to changing railway conditions. (+) Robustness due to the population-based approach. (−) Computationally expensive, requiring significant processing power and time. (−) Complex and potentially hard-to-interpret rule sets. (−) Sensitive performance to parameter choices like population size and mutation
Reinforcement Learning	(+) Allows agents to learn optimal policies through trial and error. (+) Can handle complex and dynamic environments. (−) Requires careful design of reward functions and training procedures. (−) May be slow to converge to optimal solutions.
Predictive Modeling	(+) Can anticipate disruptions and proactively adjust operations. (+) Improves system resilience and reduces delays. (−) Relies on accurate and reliable data for training. (−) May not be able to predict all types of disruptions.

Table 6. Research agenda step IV: validation and assessment.

Possible approaches	Advantages -- Disadvantages
Micro-Simulation Environment	(+) Provides a realistic testing environment for self-organising systems. (+) Allows for evaluating different scenarios and rule adaptation strategies. (−) Requires significant effort to develop and maintain. (−) May not fully capture the complexity of real-world railway operations.
Lab /test track analysis	(+) Demonstrates the feasibility and benefits of self-organisation in real-world settings. (+) Provides valuable insights into practical challenges and opportunities. (−) Requires significant resources and coordination. (−) Possible limitations of generalisation.

order to determine the most suitable method for capturing the complexities inherent in a self-organising railway system.

7.1. Definition of objectives

A crucial step in implementing an autonomous goal-oriented self-organising railway system is defining clear and measurable objectives for each level of the nested structure.

For instance, at the train level, the primary objective could be to minimise travel time while ensuring passenger comfort and safety. At the station level, the focus could shift to maximising throughput, minimising dwell times, and optimising platform assignments. At the regional level, the objective could be to maintain overall network stability, minimise delays, and ensure efficient resource utilisation across multiple stations.

These objectives, however, are not independent and often involve trade-offs. For example, minimising travel time for a single train might lead to conflicts and delays for other trains, impacting the overall network stability. Therefore, it is essential to consider the potential conflicts between objectives at different levels and establish a framework for evaluating the overall system performance based on the achievement of these objectives. This framework could involve assigning weights or priorities to different objectives, defining acceptable thresholds for performance metrics, and developing algorithms to balance competing objectives in real-time. By carefully defining and balancing these objectives, the self-organising system can ensure that the individual actions of trains and other components contribute to the overall efficiency and reliability of the railway network.

Due to the direct impact these systems have on passengers and other stakeholders, it is crucial to have the involvement of humans in defining objectives and rule development. While optimising efficiency and performance remains a primary objective, it is equally essential to consider the broader impact on all users, ensuring fairness, comfort, and accessibility (Marquis et al., 2024; Travis Fried et al., 2024). For instance, prioritising mainline trains over regional ones during disruptions, while potentially efficient, raises concerns about equitable access to transportation and the potential negative impact on regional development. Similarly, while operationally convenient, the common practice of assigning the same platforms to trains to the same destination can create accessibility challenges, especially for passengers with disabilities when they need to transfer to the assigned platforms instead of transferring the train to the more convenient platform for the passengers. Therefore, a truly effective self-organising system must balance operational efficiency with human-centric considerations, ensuring that the needs and rights of all passengers are taken into account. As shown in Table 3, the approaches for defining objectives include multi-criteria analysis and user studies, each offering different advantages and limitations beyond those detailed in the text.

7.2. Nested nature of self-organisation

Self-organisation exhibits a nested structure, with systems existing at multiple levels. The human body exemplifies this concept, being a complex self-organised system comprised of various subsystems like the respiratory and muscular systems. These subsystems are themselves self-organised entities, composed of organs, which in turn are made up of cells and even smaller components like mitochondria.

This hierarchy demonstrates a bidirectional relationship between levels. Lower-level systems self-organise and, through their interactions, define the structure and function of higher-level systems. Simultaneously, higher-level systems exert influence on lower-level ones through a process known as downward causation. This feedback loop allows for the emergence of complex behaviours and properties at each level, ultimately shaping the overall organisation and function of the system as a whole (Figure 6).
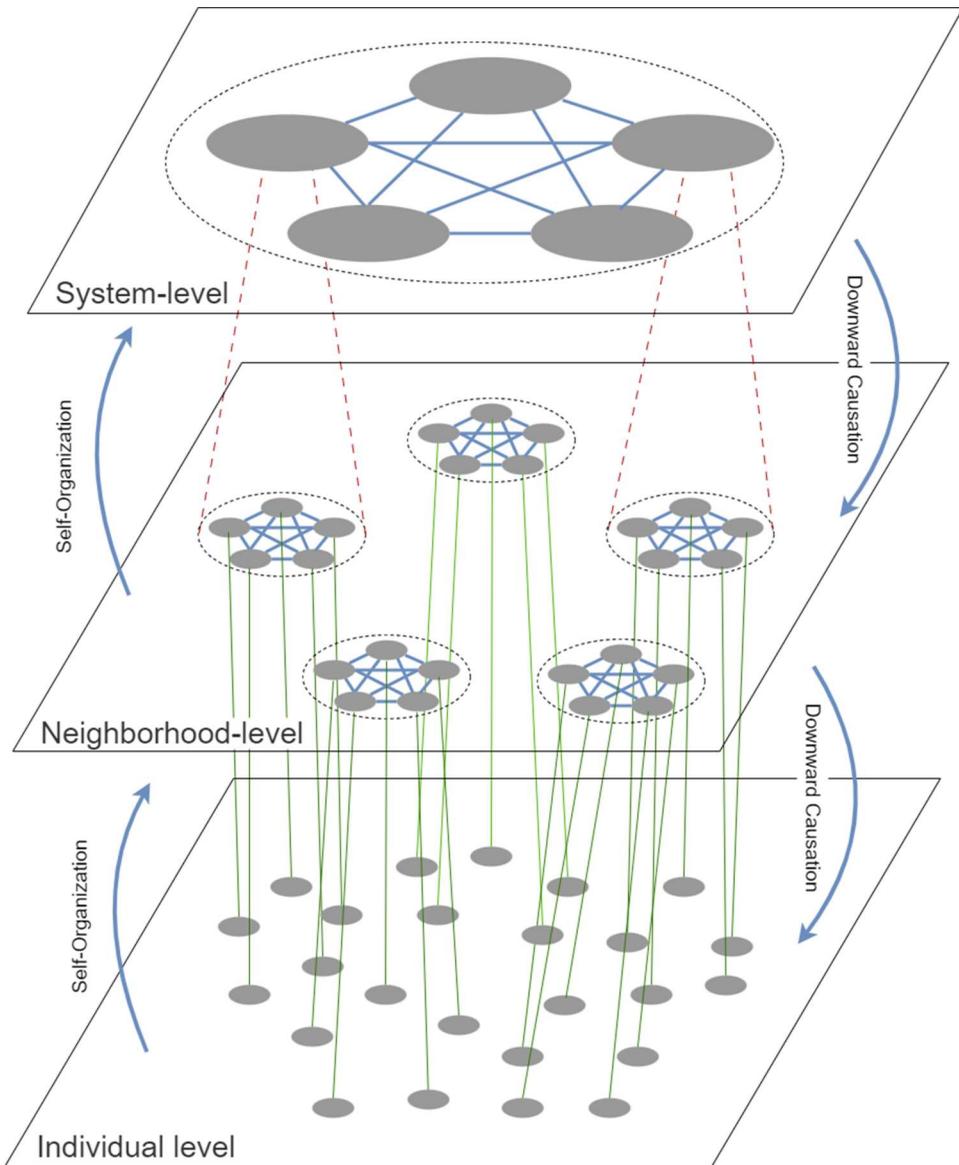
Figure 6. Nested nature of self-organisation. Self-organisation can emerge in a series of levels of organisation.

This nested structure is observed in the railway traffic system. To investigate nested self-organisation in railways, a multi-agent simulation environment may be developed to represent the railway system at various levels, including trains, stations, and regions. Each level should be modelled as a set of autonomous agents with distinct behaviours and decision-making capabilities. These agents could be trains, infrastructure or signalling components. For instance, train agents could decide on speed adjustments, route changes, or priority negotiations based on local information and interactions with other trains and infrastructure agents. Station and interlocking agents could manage

platform assignments, train scheduling, and resource allocation within their respective stations. Regional agents could oversee larger sections of the network, coordinating train movements and resolving conflicts between stations.

The interactions between agents at different levels would be governed by predefined rules and communication protocols. For example, train agents could exchange information about their positions, speeds, and intended routes with station agents, who could then use this information to optimise platform assignments and departure times. Regional agents could monitor the overall traffic flow and intervene if necessary to resolve conflicts or optimise network-wide performance. By simulating different scenarios and varying the coordination mechanisms between agents, the impact of nested self-organisation on system performance metrics such as punctuality, throughput, and energy consumption can be evaluated. This approach would provide valuable insights into the potential benefits and challenges of implementing self-organisation in real-world railway systems. Table 4 summarises the modelling approaches for capturing nested self-organisation, notably multi-agent simulation and mathematical modelling, which complement the narrative discussion.

7.3. Rule negotiation and adaptation

To develop rule negotiation and adaptation mechanisms for a self-organising railway system, a decentralised decision-making framework can be designed where agents representing trains, stations or regions, can communicate and negotiate rule changes in real-time. This framework would enable agents to exchange information about their current state, constraints, and objectives, and to propose rule modifications that would benefit them individually or collectively. For instance, a train agent experiencing a delay could negotiate with a station agent to change its platform of arrival, or a group of trains could collectively decide to reroute to avoid a congested area.

To facilitate this negotiation process, communication protocols need to be established that allow agents to exchange information efficiently and securely. These protocols should be specifically designed for self-organising systems. Game theory or optimisation techniques can then be employed to find mutually agreeable rule changes that maximise the overall system performance. For example, a cooperative game-theoretic approach could be used to find solutions that benefit all agents involved, while a multi-objective optimisation approach could be used to balance competing objectives such as minimising delays and maximising throughput. The effectiveness of these negotiation and adaptation mechanisms can be evaluated through simulations and real-world pilot projects, measuring their impact on key performance metrics such as punctuality, throughput, and energy consumption. As summarised in Table 5, possible mechanisms for rule negotiation and adaptation include decentralised decision-making frameworks, evolutionary algorithms, reinforcement learning, and predictive modelling, extending the options considered in the subsection.

7.4. Assessment through simulation

To validate the proposed self-organising railway system, simulation models of a railway network should be used. This model would incorporate realistic train dynamics, and

operational constraints, such as track layouts, speed limits, signalling systems and safety regulations. This detailed approach to understanding the impacts of all these components could be implemented by using microscopic rail traffic models. By simulating various scenarios, including varying passenger demand levels, disruptions like track closures or train breakdowns, and different rule adaptation strategies, the model can assess the system's performance under diverse conditions. The simulation results can then be analysed to identify potential challenges, such as bottlenecks, conflicts, or inefficient resource allocation. This analysis can inform the refinement of the self-organising system's design, ensuring its robustness and effectiveness in real-world scenarios.

To further validate the self-organising approach, pilot projects can be conducted on suitable railway lines or networks. These pilot projects would involve implementing the self-organising control strategies in a controlled environment, allowing for real-time monitoring and evaluation of the system's performance. Data on key performance metrics, such as punctuality, throughput, energy consumption, and user feedback, can be collected and analysed to assess the effectiveness and scalability of the approach. The pilot projects would also provide valuable insights into the practical challenges of implementing self-organisation in real-world railway operations, such as the need for robust communication infrastructure, the integration with existing systems, and the acceptance of the approach by railway operators and stakeholders. By addressing these challenges and incorporating the lessons learned from the pilot projects, the self-organising system can be further refined and optimised for wider deployment in the railway industry. Table 6 outlines validation strategies such as micro-simulation environments and lab or test-track analysis, which supplement the assessment perspectives introduced above.

Several open-source and commercial simulation platforms can support the evaluation of self-organised and decentralised railway traffic management concepts. For railway-specific studies, OpenTrack (Nash & Huerlimann, 2004), RailSys (Bendfeldt et al., 2000), and Trenissimo (De Fabris et al., 2018) are widely used for detailed microscopic simulation of train movements, signalling, and timetable stability. A more sophisticated research microscopic simulation tool that can illustrate the benefits of the AGOSO approach is EGTRAIN (Quaglietta, 2014). Agent-based modelling platforms such as AnyLogic and MATSim (Horni et al., 2016) provide flexible environments for implementing multi-agent interactions, while lightweight tools like NetLogo allow rapid prototyping of self-organising algorithms. More recently, research has explored using SUMO (Simulation of Urban Mobility Krajzewicz, 2010), originally developed for road traffic, to test multi-modal and rail–road integration scenarios. The choice of tool depends on the level of detail required: high-fidelity railway simulators are suitable for operational testing, whereas general-purpose agent-based platforms are valuable for exploring emergent behaviours in AGOSO-type systems.

8. Conclusion

This paper proposes a novel classification of self-organisation into three distinct classes: Heteronomous, Semi-autonomous, and Autonomous. This is, to our knowledge, the first explicit classification in rail that introduces AGOSO as a new class of self-organisation. It introduces the concept of autonomous goal-oriented self-organisation, defining it as the process by which a system's agents autonomously formulate, update, and adhere

to a set of interaction rules to achieve a desired goal. This framework is applied to the complex problem of railway traffic management, arguing for a self-organising approach to rule development. A model inspired by self-organisation in human societies is proposed for railway systems, detailing its key components.

This research contributes a new perspective on self-organisation in the context of railway traffic management. The proposed model, with its emphasis on autonomous rule development and adaptation, offers a promising avenue for improving the efficiency, robustness, and adaptability of railway systems. Future research should further explore the nested nature of self-organisation in railway systems, investigating how self-organising processes at different levels (train, station, region) can interact and contribute to the overall system's performance. Additionally, the development and validation of rule negotiation and adaptation mechanisms, as well as the assessment of different modelling approaches, are crucial steps towards realising the full potential of autonomous goal-oriented self-organisation in railway operations.

Regarding further research, we suggest that the nesting of self-organisation in railways systems should be addressed. This involves examining how self-organisation operates at various levels within the railway, such as trains, stations, and regions. The goal is to understand how self-organising processes at these different levels can interact and influence each other to achieve a desired overall behaviour for the entire railway network. This could involve developing a multi-agent simulation environment to model the railway system at various levels, with each level represented as a set of autonomous agents with distinct behaviours and decision-making capabilities. By simulating different scenarios and varying the coordination mechanisms between agents, researchers can evaluate the impact of nested self-organisation on system performance metrics such as punctuality, throughput, and energy consumption. This research could provide valuable insights into the potential benefits and challenges of implementing self-organisation in real-world railway systems.

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