A Unifying Framework for Self-Organization of Automated Vehicles

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ABSTRACT

In this paper we present a unifying framework for self-organization of automated vehicles. The paper is motivated by the lack of clear vision amongst researchers and practitioners on what automation and autonomy bring from a broader-than-vehicle-level perspective and how they may lead to a self-organizing logistic system. Contrary to established literature, we do not focus on automation or autonomy from a single-vehicle perspective. Instead, we offer a broad perspective on how the mutual interaction of automated vehicles will impact logistic processes. Key in our approach is the interplay between the degree of autonomy of logistic systems and their degree of cooperativeness. On these two pillars we build a unifying framework distinguishing four fundamental categories of self-organizing automated vehicles. To illustrate the working of the framework in practice, we present four real-life case studies, one per each category. The usefulness of the framework established is two-fold: (i) it provides a common ground for researchers to position their work and to identify potential future directions for research and (ii) it serves as a practical and understandable starting point for practitioners on investigating how self-organization may affect their business and where their limited resources should be focused upon.

Keywords: self-organization, logistics, transport, autonomous vehicles, framework

This research did not receive any specific grant from funding agencies in the public, commercial, or non-profit sectors.

1. INTRODUCTION AND RELATED LITERATURE

1.1 Introduction

Ever since the industrial revolution, Mankind has never ceased to embrace technology. Interestingly, technology needs technology. For instance, the technology of transport vehicles is in dire need of the technology of a highway. As more and more of our daily life is automated, complexity increases. To such a point that the human brain is either suffering from technology stress or – even worse – just cannot cope anymore. To exploit to the fullest the many features of modern transport means, we need a system to support us. Automated braking and adaptive cruise control for passenger cars and trucks are already helpful, for example. But why not delegate the entire control to some kind of autonomous system?

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In the logistic field, where efficient transport and handling are key, practitioners need to distinguish themselves by outperforming the fierce competition. Availability of human labor may be scarce, especially 24-7. Here, automated systems come to the rescue. A more advanced idea would be a self-organizing logistic system. Such a system consists of autonomous units, each with their own goal. By mutual cooperation they are able to achieve a common goal. To exemplify, the remarkable self-organization within a colony of ants forms a continuous inspiration for designing self-organizing logistic systems. Ant Colony Optimization as well as Multi Agent Systems are examples, where simple atomic entities achieve a greater goal through self-organization.

1.2 Related literature and contribution

Despite the challenge of exploring nature-inspired systems and the possibilities they bring for logistics and its future, self-organization remains relatively underexposed in the current logistic literature. Other areas of research, such as computer science and biology, have embraced the notion of self-organization and its merits. In manufacturing, within the concept of Industry 4.0, there are framework studies on the digitalization levels of companies. For instance, the paper by Bagheri et al. (2015) is one of the earliest studies where they introduce five cognitive levels in cyber-physical systems and classify them as Pure automation, Self-awareness, Self-Control. A related reference is Wang et al. (2016) who present a comprehensive framework for I4.0 digitalization. The I4.0 Readiness Framework, IMPULS by Lichtblau et al. (2015) is another comprehensive framework.

As for logistics, the need and potential to shift from conventional approaches to methods which lean towards autonomy and self-organization, is underlined throughout literature, see for example Scholz-Reiter et al. (2004), Windt and Hülsmann (2007) and Wagner and Kontny (2017). Moreover, general definitions, properties and characteristics have been studied (Di Marzo Serugendo et al., 2005), as well as design and control approaches (Gershenson, 2007). However, actual implementations of Self-Organizing Logistics (SOL) and structured methodologies or frameworks to study SOL for complex problems in logistics seem to be lacking.

A first exception, addressing Self-Organizing Logistics (SOL), is the work of Bartholdi et al. (2010), who identified advantages and disadvantages of SOL. Furthermore, they provided a practical application of SOL for assembly lines, called *bucket brigades*. In the past decade, not much was added to literature regarding the conceptualization, formalization, or practical applicability of SOL. Pan et al. (2016) provide a noteworthy attempt to further specify SOL, using the notions of openness, intelligence and decentralized control. Several authors discuss example areas of SOL, including: transportation (Hongler, et al. 2010), order fulfillment (Reaidy, et al. 2014), Physical Internet (Sallez, et al. 2015), as well as emergent behavior in supply networks (Choi et al., 2001) and parcel distribution (Quak, et al. 2019). The latter is one of the few papers combining autonomous robots with SOL, but lacks a general approach to be useful within the broader domain of transport logistics. More general approaches focus on other areas, such as - see above - cyber-physical systems (Gershenson, et al. 2019), reverse logistics (Jaaron and Backhouse, 2015) and city planning (Rauws et al., 2020). To the best of our knowledge, literature lacks an endeavor to structure the multitude of upcoming automated logistic systems with varying degrees of autonomy. This holds in particular for the rapidly expanding field of automated vehicles.

We aim to fill this void in literature by establishing a framework for self-organization of automated vehicles. Moreover, we link SOL to the irreversible uptake of vehicle automation and vehicle autonomy. Since there is some ambiguity around the notions of automation and autonomy, both in literature and practice, and in particular around the question how they may lead to a self-organizing logistic system, we touch upon these notions as well. In this paper we thus present a unifying framework for self-organization of automated vehicles. Unlike established literature, typologies and classifications, we do not focus on automation or autonomy from a single-vehicle perspective, but rather take on a broader perspective on how automated vehicles impact logistic processes. The usefulness of our framework is two-fold: (i) it provides a common ground for researchers to position their work and to identify potential future directions for research and (ii) it serves as a practical and understandable starting point for practitioners on investigating how self-organization may affect their business and where their limited resources should be focused upon.

The remainder of the paper is structured as follows. In Section 2 we discuss the notions of automation and autonomy, which are, as we will argue, closely related to self-organization in logistics. In Section 3 we provide a unifying framework for self-organization of automated vehicles, identify four levels of self-organization and discuss their impact on related notions in logistics. We illustrate the framework by means of recent case studies in Section 4. We close with conclusions and directions for further research in Section 5.

2. Aspects of Automation and Autonomy

This section aims to unify and classify various aspects of automation and autonomy, ultimately to lead to (a form) of self-organization. Before we present our framework in Section 3, we first provide a demarcation of its applicability in Section 2.1. Moreover, we discuss our views on the concepts of automation and autonomy in Section 2.2.

2.1 Demarcation

First of all, our focus is specifically on a logistical context in which automation and autonomy take place. As automation can be introduced almost anywhere in logistics, ranging from an automated workflow of document processing to automated storage and retrieval systems, we aim to clarify our exposition by providing a specific focus in which our framework is useful for both researchers and practitioners. We focus specifically on automated modes of transport. Examples would include Automated Guided Vehicles (AGVs) as used in container terminals or warehouses, Unmanned Aerial Vehicles (UAVs) for example used for surveillance or last-mile parcel delivery, and automated cargo shuttles, trains or boats. Or in one sentence: any kind of transport vehicle, regardless of modality, that can move in any (semi-)automated fashion. We leave the degree to which it can move automatically (e.g., only in some pre-defined scenarios, only closed-area or open road) part of the discussion. Notably, we argue that an increasing degree of automation has the potential (or urge) to become more autonomous and simultaneously pushes towards self-organization. Before we do so, we first define the notions of automation, autonomy and self-organization.

2.2 The Notions of Autonomy and Cooperativeness versus Automation

Both amongst researchers and practitioners there is commonly discussion around the notions of automation and autonomy and often they are intertwined. Both notions are used in different contexts and their meaning may differ depending on one's background. For example, for an automotive engineer, vehicle control might relate to concepts like steering, acceleration, braking or jerk, whilst for operations researchers, vehicle control might relate to concepts like dispatching, fleet management, routing or deadlock avoidance. Moreover, when discussing automated vehicles, an automotive engineer might solely focus on the degree to which the driving task is handed over from a human to the vehicle from a single-vehicle perspective, whereas a practitioner is interested in how an automated fleet of vehicles may improve its logistical processes. Without losing ourselves in the definition-game or discussing which definition prevails over the other, we provide our own view on both notions, for the purpose of motivating our framework for self-organization from a logistic perspective.

First, let us note that we view *the degree of automation* as the degree to which an entity is able to perform its tasks without human involvement, and *the degree of autonomy* as the degree to which an entity is capable of making decisions on its own (e.g., delegated control). Consequently, we view the degree of automation as a spectrum between zero automation (e.g., manual) and fully automated (e.g., no human involvement) in physically accomplishing a task or taking the action after the decision is made. Obviously, in practical settings these two extremes rarely occur. For example, even manually operated cars typically have automated on-board systems like cruise control, which we would position in the lower end of the automation spectrum. Similarly, the degree of autonomy is a spectrum between zero (e.g., pre-programmed or no own control) and fully autonomous (e.g., no human involvement required in making decisions in even the most extreme scenarios). Again, in practice, many systems would position themselves somewhere between these two extremes.

Second, we note that - in many cases - autonomy of a logistic system is not possible without at least some degree of automation. That is, if the system is not able to perform its core tasks (e.g., driving) to some degree automatically, it is also not capable of performing more complicated tasks (e.g., determining a route or anticipating on future demand). We say so, because in a broader logistical perspective the main achievement of an automated system is not solely eliminating a human driver or operator, but rather serving as a stepping stone towards a more intelligent transport system. That is, we typically do not deploy automated systems in practice just for being automated, but we also expect a more intelligent or robust (or any kind of metric for that matter) system compared to a manually operated system.

From this view, the notion of self-organization comes into place. As logistic systems are generally complex, interconnected systems, typically with many stakeholders, one deploys forms of automated and autonomous systems to increase productivity or streamline logistic processes. The notion of self-organization in logistics is thus one focused on automated systems (of systems) with certain decision latitudes (i.e., autonomy) in order to meet company objectives. Due to the complexity of logistic systems, a self-organizing system should be fragmented into smaller autonomous units. This is similar to how we divide a company into smaller departments (i.e., sales, inventory management, production), each which their own responsibility, but working together to achieve a common shared goal (e.g., company profit). A self-organizing logistic system is thus a system of small(er) autonomous units (also commonly referred to as agents) each with their own goal, and by communication and cooperation striving towards a common goal. Given our demarcation, this would for example be a fleet of autonomous drones for last-mile parcel delivery, which is able to perform speedy delivery without (or with minimal) supervisory or human interventions. Note that such a system is a mix of high automation (e.g., flying from any location to another in (almost) all weather conditions) and autonomy (e.g., deciding which drone delivers which parcel via which route).

Lastly, we specifically distinguish between manually organized systems and self-organized systems. One may argue that any vehicle in itself shows some form of self-organization by its driver. For example, a driver may change its route based on congestion information from a navigation system. However, we refer to this as a manually organized system, as automation is fully absent and autonomous decision-making lies fully at the responsibility of the driver. For a system to show some form of self-organization, it requires at least some automation and decision latitude outside of human control. Transitioning from manually organized systems to lowly automated systems, without sufficient autonomy, might decrease logistic performance, though. That is, humans are by nature intelligent creatures and are able to respond to changing environments. To exemplify, when a transport robot is introduced in a parcel sorting company, eliminating (unproductive) walking time by employees, performance may go down due to (i) high safety restrictions of the vehicles, lowering their flexibility and (ii) potential deadlocks at junctions. Humans may accidentally (almost) bump into each other while walking and they would never indefinitely wait at a junction when the traffic rules deployed do not prescribe who has way in a certain scenario. For an automated system to match this kind of behavior and performance, it requires advanced automated technology and also some level of autonomy to make intelligent decisions. Generally speaking, (i) there is some run-up required for an automated system and (ii) a certain level of autonomy is required to make intelligent decisions on its own, to show increased performance when moving away from a manually organized system. After this threshold is reached, opportunities arise for intelligent, automated and autonomous systems to increase the level of self-organization and to outperform manually organized systems. A general representation of this concept is given by Figure 1, where the horizontal axis denotes the degree of automation, the vertical axis the system performance measured by some relevant KPI, and the dashed line the degree of autonomy that should be associated with the corresponding degree of automation to establish a path towards self-organization. Although many different levels of autonomy might exist with the same degree of automation, the dashed line depicts what generally happens in practice.

From this figure we see that low degrees of automation with a low degree of autonomy should be avoided where possible, when implementing automated solutions, as illustrated by the example of the transport robot above.

When this is not possible, for example with pilot implementations, the run-up should be recognized by decision-makers in order to avoid loss of interest at stakeholders. Namely, after the drop in performance, which may in some cases be negligible, at some point the automated systems work sufficiently well, and some degree of autonomy can be introduced, after which performance tends to go up. From this moment onward, we talk about self-organizing logistics (SOL). Admittedly, at this point the level of SOL is extremely low, and might even perform worse than a manual system, but it is the starting point towards an ultimate form of self-organization. Although not extensively substantiated here, we expect that there is a boundary to the level of SOL given a certain automated and autonomous transport system. That is, beyond this point, further automation or delegation of control does not contribute to the self-organizing properties of the system.

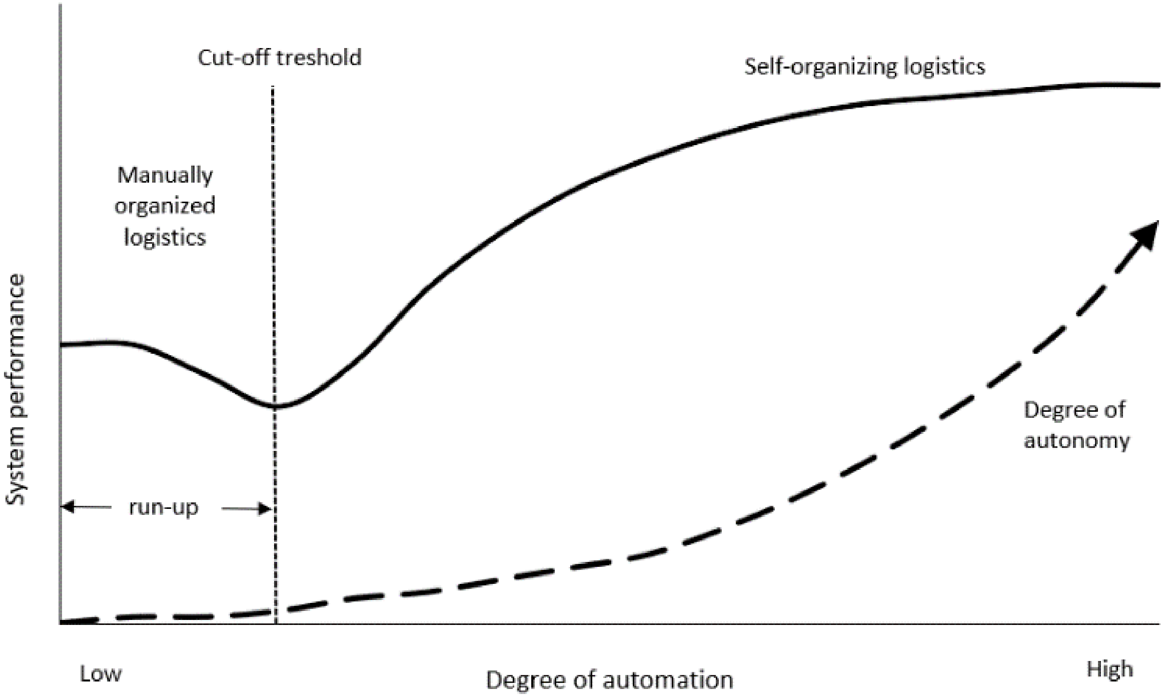

Figure 1: Co-evolution of automation and autonomy to establish self-organization.

3 A FRAMEWORK FOR SELF-ORGANIZING AUTOMATED VEHICLES

Figure 2 shows our framework for self-organizing automated vehicles. It is presented alongside the notions of (i) the degree of autonomy and (ii) the degree of cooperativeness, both of which are discussed in Section 3.1. The descriptions alongside the axes of the framework aim to provide general categorizations, as such to be applicable to a broad spectrum of autonomous transport solutions (e.g., vehicles, drones, boats or delivery robots). Moreover, the framework identifies four areas to help classify research in the field of self-organizing automated vehicles. The four areas are discussed in Sections 3.1.1 to 3.1.4. The boundaries between these areas are far from rigid, but they help to provide researchers and practitioners with a common ground and vocabulary to guide the discussion of self-organizing automated vehicles. Moreover, they suggest directions for research and help to shape roadmaps towards self-organization of automated vehicles. The shaded area represents our view on the path towards self-organizing automated vehicles, having clearly demarcated, lowly self-organizing systems near the origin and loosely coupled, highly self-organizing systems when approaching the top right. These and related concepts in logistics are further discussed in Section 3.2.

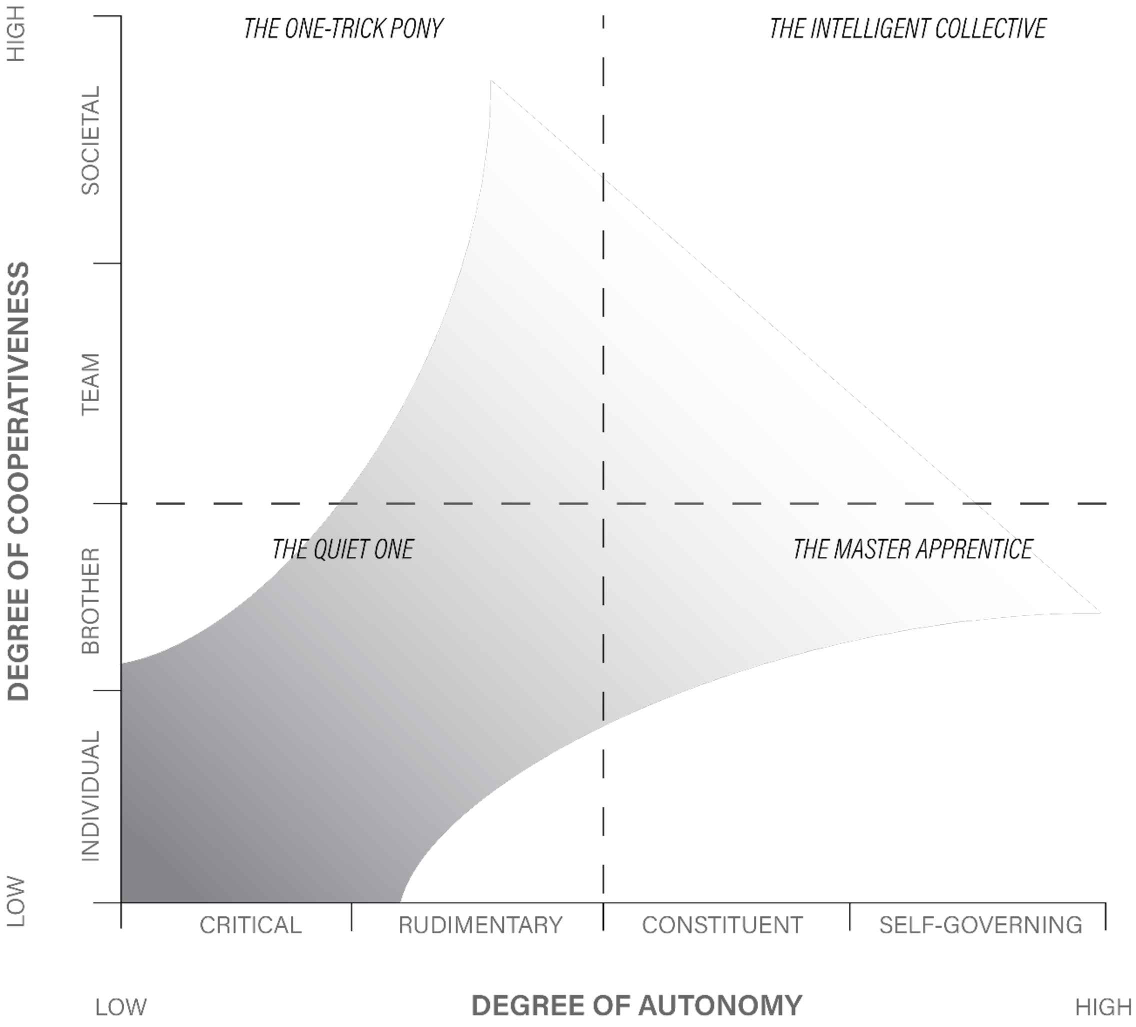

Figure 2: Framework for self-organizing automated vehicles.

As the concrete interpretation of both the descriptors alongside the axes and the identified areas are highly case specific, we provide examples of the application of the framework to real-life cases in Section 4 and use somewhat agnostic descriptors in the framework itself, albeit within the domain of automated transport.

The authors believe that this approach makes the framework useful to fit a broad spectrum of (future) cases for self-organizing automated vehicles, without losing generality.

3.1 Autonomy versus Cooperativeness

The framework for self-organizing automated vehicles as shown in Figure 2 is plotted along two axes: degree of autonomy and degree of cooperativeness. We argue that these two elements are inherent to SOL as there is always a certain tension between autonomy and cooperativeness of any system whatsoever. European countries, for instance, take pride in keeping their autonomy, but - at the same time - sacrifice it somewhat in order to benefit from fruitful cooperation with European partners. In the logistic field, major shipping companies formed the Grand Alliance. Cooperation among members is restricted to provision of joint port-to-port services. The shipping lines stay autonomous and compete to attract customers.

In general, any cooperative project must be based on a clear convergence of goals. A logistic system with a low degree of autonomy will probably easily cooperate with a similar partner since the goals will quickly converge. For instance, fire brigades easily cooperate. Their common goal is obvious. On the other hand, logistic systems with a high degree of autonomy need a long trajectory to achieve cooperation (e.g. KLM and Air France). Hence, in Figure 2, highly self-organizing transport systems will experience a challenging route towards cooperation.

For the degree of autonomy, we divide the scale from low to high into four levels: (i) critical, (ii) rudimentary, (iii) constituent and (iv) self-governing. The first level comprises of automated systems where the only autonomy is focused on tasks that are critical or safety-related (e.g., avoid imminent danger or collisions with humans). Within the second level, some additional, rudimentary tasks are given to vehicles to decide upon (e.g., follow a pre-defined route or return to a base station). Within the third level, the majority of the tasks can be performed autonomously, but supervisory human control may be required in some scenarios. One may think of determining a route based on real-time congestion information or reroute to a charging station. However, the most difficult tasks are not performed autonomously by the vehicles, but rather by a human or external software.

The last level consists of systems where all, or close to all, tasks are performed autonomously and the responsibility (or decision latitude) lies fully at the autonomous transport system. It goes without saying that typically in such self-governing systems the human role is not fully absent. For some situations human control may be beneficiary for the system. Furthermore, within each level there is some room for interpretation. For example, one may position its system on the boundary between two levels. In Section 4 we provide case studies to illustrate this.

Also, the degree of cooperativeness is divided into four levels: (i) individual, (ii) brother, (iii) team and (iv) societal. The first level are systems where the autonomy (any degree of it) lies within a single unit and there is no cooperation between the units. Within the second level there is some level of cooperation, but only between the same type of transport units or within a quite narrow set (i.e., brothers). Within the third level, the degree of cooperativeness is extended beyond the borders of like-minded transport units and now includes cooperation between other system functionalities (e.g., cooperation between routing, scheduling and battery replenishment to determine effective routes, whilst respecting time-windows and simultaneously taking into account energy levels of the vehicles and the capacity of charging stations). A team still operates within the boundaries of a single company (e.g., a fleet of AGVs at a container terminal).

Within the last level, the cooperation goes beyond the boundaries of a single company and we classify these autonomous transport systems as societal. That is, within a certain logistic system, the entire (or vast majority) of the society (e.g., stakeholders or processes) cooperatively manages the logistic system. An example would include a fleet of autonomous trucks who cooperate with traffic lights to optimize the flow of traffic. One may also view this as a set of sub-units working together to manage the logistic chain. Again, the interpretation of the levels may be case-specific and is further discussed in Section 4.

Before we do so, we first introduce four categories of SOL within the framework, each with certain degrees of autonomy and cooperativeness. These categories motivate the name we will henceforth give to our framework: the SOL framework

3.1.1 The Quiet One

In the lower-left quadrant of Figure 2 we identify both the degrees of cooperativeness and autonomy as low and denote this category by *The Quiet One*. This denotation comes from the fact that the transport systems classified in this quadrant typically perform their tasks in relative solitude with no to little communication with others. These - although typically automated - systems show no form of autonomy or only for safety-critical or rudimentary tasks. These systems typically consist of a homogeneous fleet of vehicles, where each unit works independently with zero to almost no cooperation between vehicles. Examples would include automated warehouses where pallets are moved around using robots, or reconnaissance drones which map pre-programmed areas. All decisions within these logistic processes (e.g., what to do when) are determined - not by the vehicles themselves but - by either a human controller or a centralized system. In these systems, the decision latitude is very low to low, with no to little connection between the transport units or with external systems. As a collective, such systems may still be highly-efficient and intelligent. The intelligence then emerges from a system level in a more-or-less centralized fashion. These systems are typically highly coupled and clearly demarcated, which are preferred properties for stability and predictability, but show no to little emergent behavior nor contain much self-organizing properties.

3.1.2 The Master Apprentice

We denote lowly cooperative but medium to highly autonomous systems by *The Master Apprentice*. Similar to the previous category, the degree of cooperativeness is low to limited, but the transport units have a substantial amount of autonomy. This ranges from partly delegated control to fully self-governing. An example would include a fleet of vehicles that is highly to fully responsible for carrying out all, to almost all tasks, without supervisory control (e.g., scheduling, routing, conflict resolution, recharging, maintenance activities, etc.). These systems show some form of self-organization, mainly due to their autonomous nature, but typically within a limited scope or application area. There is no connection or cooperation with external systems or awareness of the broader impact of their actions. This may include for example a fleet of autonomous parcel delivery drones, where last-mile logistics is fully self-governing and parcels are delivered in a timely fashion, with a minimum number of vehicles deployed. However, the system is not aware of any customer-related preferences and thus may fail to provide the best service possible from a customer point-of-view. For example, the system is not aware of the customer's whereabouts and thus may face a no-show or is not able to adapt the delivery location based on the customer's presence. However, within their limited domain of cooperation, these systems perform well with no to little (human) supervisory control required. As the decision latitude increases, the intelligence moves from a system level to the autonomous units.

3.1.3 The One-Trick Pony

In the upper-left quadrant of the framework we identify lowly autonomous and medium to highly cooperative systems and denote these by *The One-Trick Pony*. This designation is motivated by the fact that the transport systems in this quadrant typically have a limited set of skills. They score low on autonomy which is confined to safety-critical or rudimentary tasks. Their degree of cooperativeness, however, is high. The latter enables them to communicate with their environment, e.g., with external logistic systems. Opposed to the previous two categories, these systems cooperate beyond the borders of their own span of control to form collaborations. They may consist of a heterogeneous fleet of vehicles that mutually cooperate.

Despite a substantial amount of cooperation, the nature of the cooperative tasks is limited to basic or rudimentary tasks, but still may yield a highly efficient system. An example would include a fleet of autonomous vehicles which may adapt their routing based on current congestion information or synchromodal systems which base their decisions on real-time information.

A concrete example for the latter case would include the last-mile parcel delivery example of the previous category, where now both street robots and drones are available. Both modalities communicate and coordinate to provide a cooperative delivery service. For example, a drone might be less suitable in bad weather conditions, whereas the street robots are less suitable in areas with bad infrastructure. As system boundaries become increasingly ambiguous when cooperating with other parties or (IT-)systems, the predictability may go down when moving away from closed systems. Moreover, notions as trust, vulnerability and responsibility come into play as existing cooperative partners may change their mind, leave the system or are replaced by other partners with different interests. However, as the decision latitude is low for this category, the impact of these notions is expected to be small and thus may provide a safe haven as a step towards SOL for systems currently identified as *The Quiet One*.

3.1.4 The Intelligent Collective

In the last category both the degree of cooperativeness and the degree of autonomy is medium to high. Self-governing autonomous systems which cooperate with a large part of the society fall within this category. Decisions are made autonomously, and tasks are performed via mutual cooperation and coordination. Therefore, we denote this category by *The Intelligent Collective*. In this category there is a high delegation of control which spans beyond the boundaries of a closed domain by cooperating with external actors or systems. The top-right corner of this category includes extreme forms of SOL and shows similar self-organizing properties and emergent behavior as biological systems, like ant colonies and beehives. A fleet of self-organizing vehicles complements the notion of the Physical Internet (PI). The idea of PI is to place goods in standard boxes containing encapsulated information, usually via Internet of Things (IoT) to identify the package and to route it to the right destination. IoT refers to a concept where every-day physical objects (so-called things) are connected to the Internet and are able to identify themselves to other devices, collecting and sharing data. Here, a ‘thing’ is an object that is traditionally not connected to the Internet, such as a garage door, a utility meter, a streetlamp, etc. Connecting these ordinary things to the Internet enables them to communicate with each other real-time without any human being involved, thus effectively merging the digital and physical worlds (i.e., transport by automated vehicles). The intelligence acquired by the objects may vary between merely identifying themselves (e.g., by RFID) and making smart choices (based on built-in software).

Other, less extreme, examples of systems within *The Intelligent Collective* would include coordination between manual and autonomous vehicles in mixed-traffic applications and real-time collaborative transport planning.

3.2 Beyond the SOL framework

The framework presents four categories of SOL and helps researchers and practitioners to position their research and projects. Moreover, the framework is useful to position the implications of SOL on related concepts in logistics. For example, the shape of the shaded area in Figure 2 denotes the paths that lead to more self-organizing systems. In addition, the shade of grey denotes the corresponding transition from closed, highly coupled systems near the origin, towards open, loosely coupled systems identified as *The Intelligence Collective*.

In this section, let us consider other relevant notions in logistics that are affected by self-organization. We illustrate them in Figure 3 by means of contour plots (the whiter the shade, the higher the value). Similar to Figure 2, the degree of autonomy is shown on the horizontal axis and the degree of cooperativeness on the vertical axis. Although many concepts and notions exist within the field of logistics (cf Pan et al. (2016)), we argue that the following notions are affected most by self-organization: (i) control hierarchy, (ii) intelligence, (iii) predictability, (iv) connectivity, (v) decision latitude and (vi) cost-effectiveness. In particular, the control hierarchy is highly affected by self-organization, shifting from centrally organized systems to decentralized systems. Due to this shift, the notions (ii)-(vi) are also affected. These notions are further discussed below.

Control Hierarchy

Systems positioned in the top-right quadrant (The Intelligent Collective) make their decisions autonomously and tasks are performed via mutual cooperation. There is a high delegation of control by cooperating with external systems. So, this quadrant is leading with regard to decentralized control. When cooperation is high, but the extent to which decisions are made autonomously is low (i.e., the top-left quadrant) there is still a high reliance on centralized (or human) control. In this quadrant thus more hybrid control hierarchies are expected.

Intelligence

The modes of transport in the logistic systems in the lower left quadrant (The Quiet One) have little to no individual intelligence. As these systems are typically controlled centrally, intelligence may stay confined to system level. For individual intelligence, a logistic system needs to be sufficiently cooperative. That is why the upper quadrants score higher on intelligence emerging from a collective level, rather than a system level. To a lesser degree this also holds for *The Master Apprentice* (i.e., a dark shade of grey) and *The One-Trick Pony* (i.e., a light shade of grey), resulting in a hybrid system, where intelligence emerges both on a system level as well as on a collective level.

Predictability
Figure 3c is the opposite from Figure 3a (Control Hierarchy). Since systems positioned in the top-right quadrant (The Intelligent Collective) make their decisions fully autonomously and by cooperation, they are hard to predict for the outsider. In contrast to this, the logistic systems from The Quiet One are highly predictable.

Connectivity
Inherent to cooperation is the ability to communicate, which – for autonomous systems – originates from IT-systems. The framework distinguishes between communication with internal systems (i.e., up until brother level) and the ability to communicate with external systems (i.e., team level and above). Figure 3d shows the expected impact of the degree of cooperativeness of the autonomous system. In the lower half of the framework the connectivity is expected to be low, as no or little cooperation is required. From there on the level of connectivity increases and is especially high when cooperation is sought within the entire society. A similar plot can be made regarding the vulnerability of the system.

Decision-latitude
In order to have decision-latitude, a logistic system needs to be sufficiently autonomous. That is why, only systems from The Intelligent Collective and The Master Apprentice have this privilege.

Cost-effectiveness
Logistic systems in the lower left quadrant (The Quiet One) have hardly any decision latitude. They do not require a huge investment per vehicle, which enables the procurement of several coupled systems which - together - are highly cost-effective. Conversely, systems from the top-right quadrant are quite expensive per vehicle. Nevertheless, for huge companies that can afford them, these self-governing autonomous systems really make a difference by cooperating with important societal partners. Hence, they are cost-effective as well.

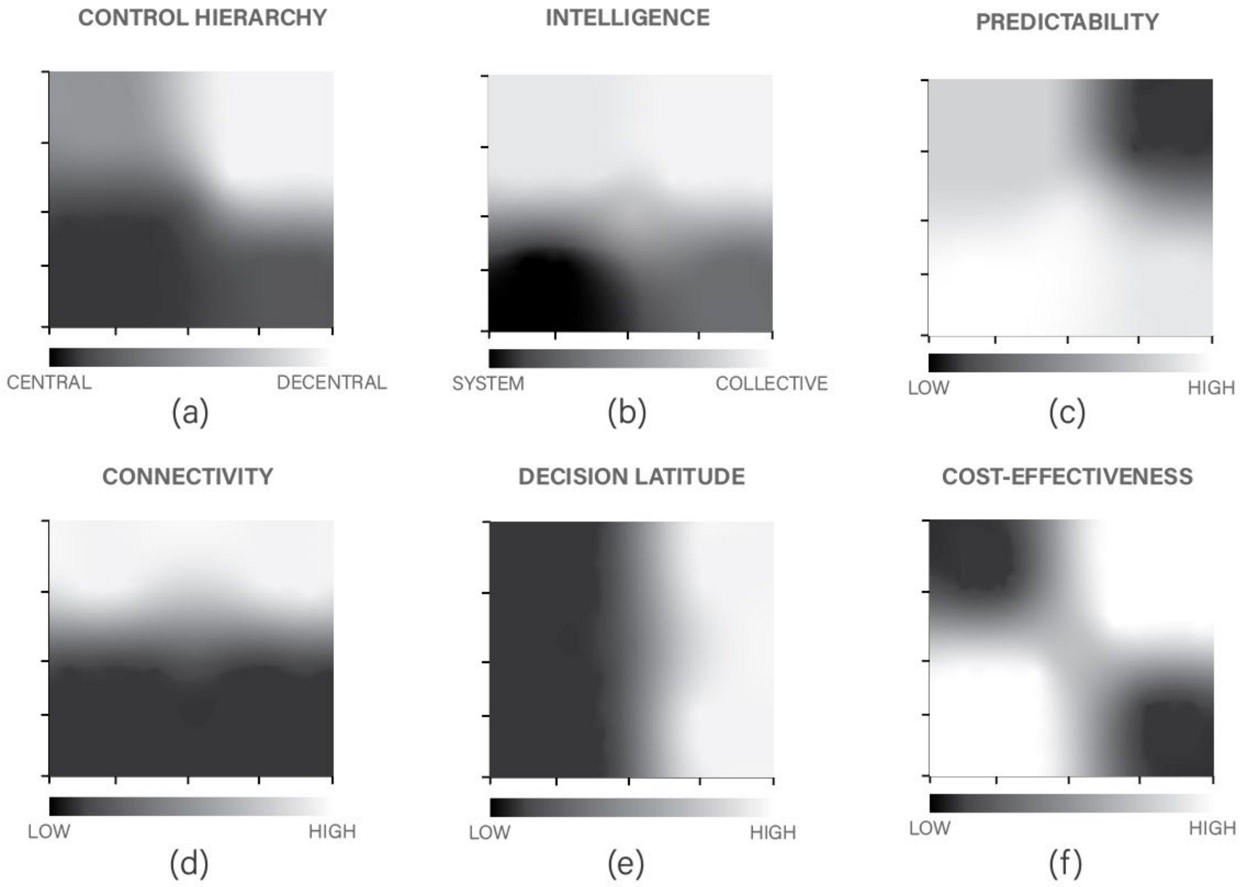

Figure 3: Impact of SOL on related notions in logistics.

4. CASE STUDIES

This section presents four real-life case studies to illustrate the usability of the SOL framework. For brevity we provide only short introductions to the cases. In the sections below, we discuss the following three aspects for each case study: (i) the case is positioned within the framework, (ii) one or more opportunities are provided to increase the level of self-organization and (iii) the limits of SOL are discussed. Figure 4 shows the SOL framework with the positioning of the case studies (denoted by the number of the case study) as they are now, and it also depicts the directions towards more self-organization.

Case 1: Manure cleaning robots

The first case study underlines the broad spectrum in which the SOL framework can be applied. This case focuses on the agricultural sector and specifically on the logistics of manure cleaning robots in cow stables. These robots sweep the barn for manure using pre-defined routes and deliver the manure to a fixed location. Each robot has a dedicated charging station to recharge the battery. Depending on the size of the barn, one to six robots are deployed simultaneously. When multiple robots are deployed, they each have a unique (non-overlapping) section of the barn to clean.

Despite the high automation degree of these robots, the level of autonomy is low. The robots are able to sense objects in their close surroundings using ultrasonic sensors. The robots stop when a non-preprogrammed object is detected for a longer time period and thus perform critical safety tasks by themselves. The only two other (rudimentary) tasks the robot takes are: (i) drive to the charging station when the battery is nearly depleted and (ii) drive to the manure-delivery location when the tank is almost full. Both decisions are based on pre-programmed routes and logic. The decision latitude of the robots is thus quite low and there is no cooperation between the robots when multiple are deployed.

We thus categorize the automated logistic system of this case study as *The Quiet One* with no self-organizing properties. A direction to enhance self-organization includes the combination of: (i) delegate more tasks to the robots with supervisory control by the farmer,e.g., the vehicles determine their own routes and charging schedules within the time limits set by the supervisor, and (ii) introduce cooperation between the robots to relax the restriction of unique sections such that robots can for example take over jobs when one is temporarily out of service. An additional opportunity to enhance self-organization is to include a cow monitoring system to measure and predict manure intensities in different areas of the stable. When such a monitoring system cooperates with the robots, a more connected and flexible system is created which surely outperforms the non-cooperative variant of the system.

Both these directions towards SOL are shown in Figure 4, where the latter option is within *The Intelligent Collective* category, near the center of the framework. Further increasing cooperation or autonomy within this case study does not seem worthwhile or useful in practice and thus the ability for the system to become self-organizing is deemed present but limited.

Case 2: Truck Platooning

The second case study is focused on truck platooning. Truck platooning is a recently developed technology within the logistic sector. In a platoon, two or more digitally connected trucks drive in a convoy with small following distances in a (semi)autonomous fashion. In this case we specially focus on so-called real-time platooning, where platoons may be formed close before the scheduled departure of a truck. Example locations would include parking areas or fuel stations. The interested reader is referred to Gerrits (2019) and Gerrits et al. (2020) for a more detailed discussion. Trucks at these locations are typically from different companies. The trucks may cooperate and try to find suitable matches to form a platoon with, and therefore jointly benefit from fuel and emission savings. The trucks still need a human controller, or at least a human supervisor. They also cooperate with external systems, e.g., they make way when a non-platooning vehicle enters the highway or connect to intelligent traffic lights. By cooperating they bundle forces. This case demonstrates that a certain degree of cooperativeness between different trucks and/or companies results in a more efficient logistic system with mutually shared benefits. The level of autonomy is low as trucks are not allowed to radically change their course of action, e.g., routes or time-windows. Despite this limited decision latitude, truck platooning still shows its usefulness within the logistic sector. This case can clearly be considered as a One-Trick Pony.

Further increasing cooperation among truck companies - by for example aligning routes or schedules in real-time - may provide opportunities for enhanced self-organization within truck platooning, beyond solely driving together when an opportunity arises. Moreover, more control can be delegated to the trucks to make decisions in real-time. For example, a truck parking area may provide opportunities for trucks to collaborate to solve less-than-truckload shipping when two or more loads can be consolidated in a single truck. Obviously, a mutually agreed upon cost-benefit sharing system needs to be deployed in any situation. When trucks are allowed to make more decisions autonomously and in real-time, we move away from static planning by each individual truck company, towards a more self-governing and societal transport system, beyond truck platooning alone. This path towards SOL is illustrated in Figure 4.

Case 3: Smart Yards

The third case study focuses on low-speed autonomous vehicles in closed or semi-open areas at or near distribution centers or other transport hubs. Examples include: (i) the landside area of a cargo airport, (ii) pre-gates parking areas or buffer zones at container terminals and ports and (iii) aprons at the docks of a distribution center. For a more in-depth analysis of the latter case, the interested reader is referred to Gerrits et al. (2018). These cases provide opportunities for the hand-over of cargo (e.g., containers or trailers) to autonomous vehicles for last-mile transport or on-site maneuvering. Hence, we refer to these areas as *Smart Yards*. They not only provide a decoupling point between last-mile and long-haul, but also provide opportunities for autonomous freight transport. Typically, yard tractors or similar vehicles are deployed in these areas. Multiple manufacturers are currently developing and testing a next generation with a high degree of automation, so-called Automated Yard Tractors (AYTs). These AYTs enable unmanned last-mile transport and maneuvering and provide opportunities for delegated control. In this case study, we are particularly interested in how a fleet of AYTs is able to handle the logistic processes at yards in an autonomous and ultimately self-organizing manner.

AYTs are highly automated and are able to drive in both closed areas as well as on (semi-public) open roads. Opposed to Case 1, where we see a similar degree of automation, AYTs are developed with autonomous task handling in mind. That is, the purpose of AYTs is not to solely replace human drivers or operators, but also to take over tasks such as routing, scheduling and conflict resolution. This is possible as a fleet of AYTs is typically homogeneous and has a clearly demarcated set of tasks to perform within the last-mile. The sole purpose of an AYT is to fulfill transport requests from origin to destination based on inbound and outbound transports. Depending on the specific case location, this ranges from low-speed maneuvering on closed aprons near the dock area to medium-speed driving between terminals or pre-gate parking areas. The freedom of the AYTs is currently bounded by external systems or infrastructural limitations. The system does not have any influence on these external mechanisms and thus we classify autonomous vehicles at smart yards as *The Master Apprentice*. In terms of autonomy we classify smart yards on the verge of constituent and self-governing and in terms of cooperativeness on the level of brother (i.e., the fleet of homogeneous AYTs form a strong bond).

To increase SOL within this case, we identify the possibility of including more cooperativeness with external systems. Currently, the fleet management of AYTs is typically determined by a centralized system which accounts for transport planning. When a more connected and cooperative system is deployed, e.g., by using IoT-sensors, geo-fencing or coupling with warehouse management systems or terminal operating systems, the fleet of AYTs may be able to make smart decisions based on the data generated. For example, non-urgent transport may be brought forward in the planning when some AYTs are idling, to increase available capacity when more demand is anticipated in the future given. Also, AYTs may position themselves strategically when a geo-fencing system is deployed in order to reduce waiting times. This enhanced degree of cooperativeness automatically provides opportunities for the system to become more self-governing in terms of autonomy, thereby reducing the role of human planning to make operational decisions.

For a smart yard to become more societal beyond this point, we propose to also cooperate with infrastructure such as Intelligent Traffic Lights (ITLs). When AYTs are able to communicate with ITLs in mixed-traffic open road situations, the traffic monitoring system may be able to secure junctions. With this cooperative behavior, the external traffic system thus influences the self-organizing properties of the AYT system, especially in terms of safety. The degree of cooperativeness takes a rather large leap as this requires cooperation beyond the logistic processes of a smart yard. The degree of autonomy, however, does not change much with this added functionality, which from a safety perspective may be useful. From an SOL perspective we position this additional cooperation on top of the previously mentioned cooperativeness with external systems, as shown in Figure 4.

Case 4: Mixed-Traffic Container Terminals

The final case study is also focused on the deployment of AYTs, as introduced in the previous case study, but in this case in Mixed-Traffic container Terminals (MTTs). This case study presents a near-future vision of Automated Container Terminals (ACTs), where both AYTs and manual trucks coexist. The AYTs have similar tasks as in the previous case: providing horizontal transport, between the quay area and the stacks of a terminal. In an MTT (see Gerrits et al. (2019) and Gerrits et al. (2021) for further details), manually operated road trucks share the same infrastructure with the AYTs. For an MTT to be safe, secure and performant, a high level of autonomy and cooperation is required. Even in non-mixed-traffic terminals, AYTs may be highly autonomous in their decision-making (e.g., routing, scheduling, charging) in order to facilitate high terminal productivity. When introducing mixed-traffic, even more control should be delegated to the fleet, in order to attain a robust, safe and most-of-all, scalable system. Typically, 5-10 AYTs are deployed per quay crane and thus - even for mid-sized terminals planning & control in real-time is challenging and global optimization methods are less suitable. Moreover, trade-offs between manual and automated vehicles are imminent in mixed-traffic situations and thus a high degree of cooperativeness is required to guarantee safety and efficiency. ACTs with mixed traffic can thus be positioned with high degrees of both autonomy and cooperativeness, as shown in Figure 4.

For the system to become more self-organizing, the crux is the harmony between the manual and the automated systems. Only in harmony, the system may be fully self-governing. For example, in order to increase port productivity, dynamic traffic rules may be deployed based on terminal congestion. Whilst dynamic control of the terminal may be beneficial, it may also introduce unpredictability (e.g., a dynamic limit on the number of manual trucks allowed on the terminal during peak hours). These rules should be clearly communicated to both the manual and automated system. In future applications, AYTs may even be allowed to leave the terminal area. For example, to provide last-mile shuttle services between terminals and pre-gate parking areas. For now, AYTs are not allowed to leave the terminal and thus the societal level of cooperativeness cannot be reached as the terminal remains a closed area.

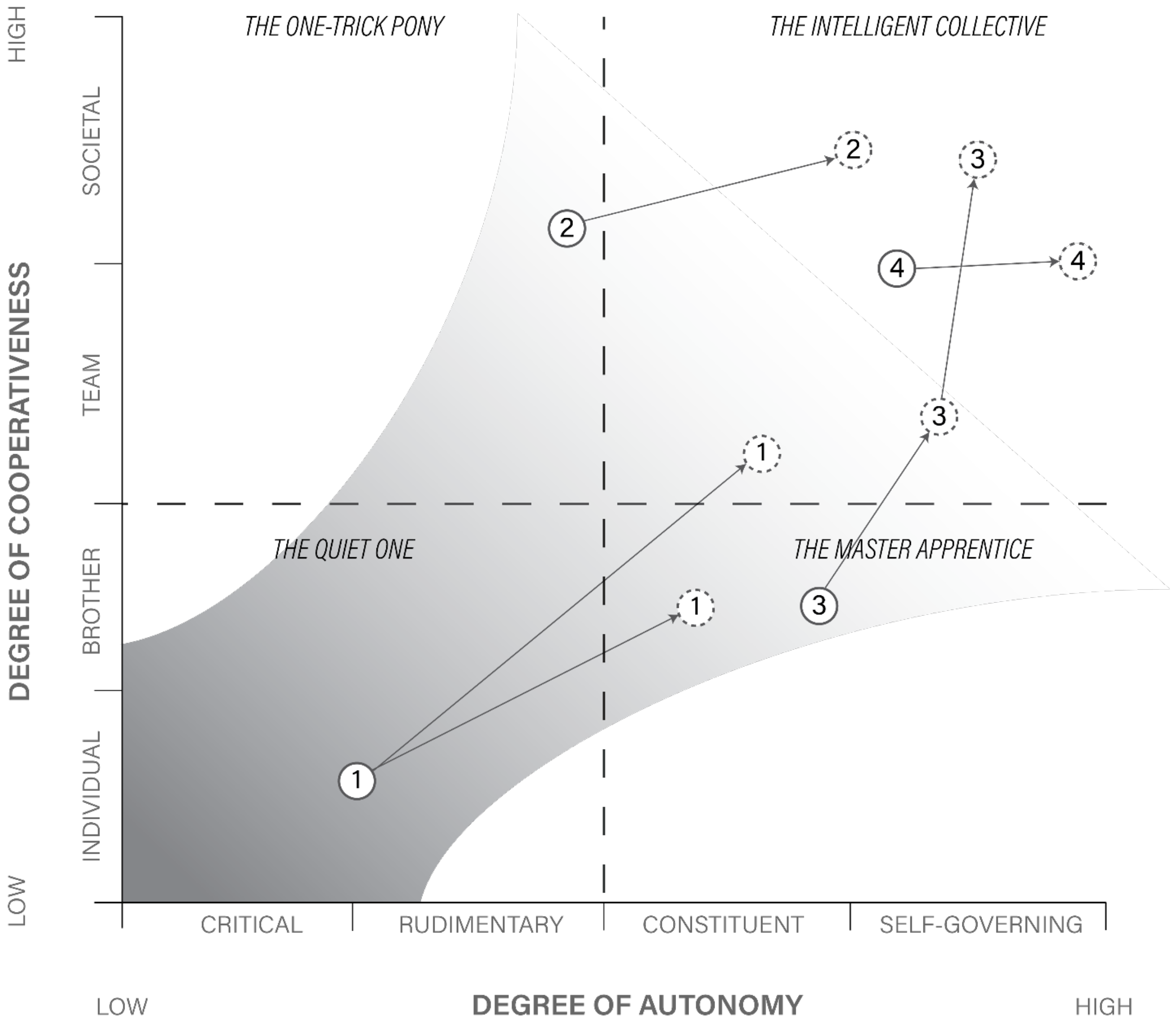

Figure 4: Case studies positioned within the SOL framework.

5. CONCLUSIONS AND FURTHER RESEARCH

This paper presents a unifying framework for self-organization in the field of automated vehicles offering a broad perspective on how automated vehicles impact logistic processes. The framework focuses on the interplay between the degree of autonomy (DA) of logistic systems and their degree of cooperativeness (DC). In the corresponding perceptual mapping, the following four quadrants can be distinguished: (1) The Quiet One (low DA, low DC) (2) The Master Apprentice (high DA, low DC) (3) The One-Trick Pony (low DA, high DC) and (4) The Intelligent Collective (high DA, high DC). These four categories of self-organizing automated vehicles help researchers and practitioners to position their research and projects.

The framework is also useful to position the implications of SOL on related concepts in logistics. We illustrate this by contour plots, where the impact of the DA and the DC is shown for six related notions in logistics: (i) control hierarchy, (ii) intelligence, (iii) predictability, (iv) connectivity, (v) decision latitude and (vi) cost-effectiveness. The framework is illustrated by means of four different case studies from practice.

The usefulness of the established framework is two-fold: (i) it provides a common ground for researchers to position their work and to identify potential future directions for research and (ii) it serves as a practical and understandable starting point to create awareness for practitioners on how self-organization may affect their business and where their limited resources should be focused upon.

We challenge researchers to use this framework to position their research and to steer their investigations towards interesting areas. As future research, we intend to include case studies into other types of modalities to further verify our framework. In particular, since all case studies mentioned involve ground vehicles, it may be interesting to perform case studies into unmanned aircraft.

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