Swarm Intelligence and Systems Thinking: Finding Common Ground for the Engineering of Drone Swarms Solutions

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Abstract

Swarm intelligence (SI), inspired by the collective behaviour of social insects, such as ants, bees, and termites, has been applied to various domains, including the engineering of drone swarms. Another holistic approach to understand and design complex systems is systems thinking (ST), which emphasizes particularly the interactions and relationships between a system's components. This paper explores the intersection of SI and ST, aiming to find commonalities and synergies between the two fields. Based on previous research, the paper highlights the key characteristics (e.g., decentralization, self-organization, and adaptability) of the bio-inspired bottom-up approach of SI and compares them with the core features (such as interconnectedness and feedback loops) of top-down type of ST. By integrating concepts and principles from both disciplines, the paper suggests that innovative solutions to complex problems, for instance, in the engineering of drone swarms, can be developed. The paper concludes that both approaches share a focus on emergent behaviour and the importance of considering a system as a whole. The combined application of both of them can eventually lead to a better understanding, design and management of complex artificial systems, such as drone swarm solutions.

1. Introduction

Understanding, designing, and managing the behaviour of a drone swarm in its real-world operational environment remains a central challenge in the field of unmanned aerial systems (UAS). As the environments and tasking systems for drone swarms grow in scale and interconnectivity, traditional linear models often fall short in capturing their dynamic, emergent behaviours. This challenge is particularly pressing in domains, such as wildfire response, where the drones, their human operators, and other relevant stakeholders (e.g., the fire crews) must adapt in real time to the changing natural environment. Addressing this complexity is not only a technical imperative but also a societal one, with implications for labour safety, environmental sustainability, and community resilience.

A prominent paradigm in the engineering of drone swarm solutions is swarm intelligence (SI, see e.g., Bonabeau et al., 1999; Kennedy and Eberhart, 2001; and Garnier et al. 2007). It has typically been inspired by the collective behaviour of social animals like ants, birds, and fish. Recently, SI has been applied, for instance, to drone swarm coordination (Saffre et al., 2021), human behavioural analysis (Ylisiurua, 2024), industrial robots (Cheraghi et al., 2021), network routing (Zungeru et al., 2021), and collective decision-making (e.g., Prasetyo et al., 2019). However, SI systems in vivo do not often map to SI systems in silico directly: for instance, in contrast to simulations, the size of a beehive or ant colony is not inherently scalable to infinity. In the context of drones, artificial SI models are therefore typically scaled from a few to dozens or even hundreds of relatively similar agents, capable of functioning equally effectively. SI systems are thus characterized by decentralized self-organization, where behaviours emerge from adaptive rules in local interactions among simple agents. As the size of the swarm increases, in principle the system can often maintain its performance or even improve in certain cases due to increased diversity and redundancy (Bjerknes & Winfield, 2013).

In this paper, we reflect another holistic approach to understanding, modelling and designing complex socio-technical systems called systems thinking (ST, Senge, 1990) and consider how it could be utilized in the engineering of drone swarm solutions. Similarly to SI, ST emphasizes the interactions and relationships between a system's components. However, a "system" in the ST context can entail various kinds of constituents from a hospital to a human's digestive system. ST has been previously applied successfully, for instance, in ecology (e.g., Orr et al., 2008), economics (e.g., Valentinov et al., 2015), and healthcare (e.g., Trbovich, 2014). This large variety of application areas is possible, because ST models operate at a higher level of abstraction, focusing on aggregate behaviours and system-wide dynamics (Strijbos, 2010). They aim to capture the big-picture behaviour of the system, focusing on a limited number of conceptualized agents to understand the system's overall structure and feedback loops (Sterman, 2000).

Whereas SI is a paradigm for operation, ST is more of a conceptual framework for analysis, helping practitioners to anticipate unintended consequences and design more robust systems. ST aids particularly in the development of more potent approaches to resolving systemic challenges and understanding of complicated problems by helping people and organizations foresee unexpected system-level effects. In detail, core features of ST include (based on Senge, 1990 and Sterman, 2000):

1. **Holistic perspective**: Systems are viewed as wholes, recognizing that a system's behaviour is determined by the interactions between its constituent parts (that are defined more broadly than as a collection of agents).
2. **Interconnectedness**: The interdependence of a system's parts is emphasized, acknowledging that changes to one part can have a significant effect on the system as a whole.
3. **Feedback loops**: System feedback loops can gradually intensify (reinforce) or stabilize (balance) system activity. They can push the system further in the direction of the initial change, or pull the system back, resisting change.

4. **Emergence**: Systems have emergent properties, forcing an analysis of a system beyond its individual component pieces towards the behaviours and properties of the whole.
5. **Dynamic complexity**: Systems undergo gradual evolution in response to both internal and external influences.

As can be noted from the features, SI and ST are not alternative or competing design choices. While both SI and ST originate from complex systems science, they have largely evolved in parallel. SI focuses on operational mechanisms for distributed coordination, whereas ST provides analytical tools for systemic insight, helping to understand structure and introduce strategy and control (also potentially to autonomous systems). Despite their complementary strengths, their integration in the context of engineering swarm robotics, remains underexplored.

The present paper aims to close this gap by addressing the open question of how ST can inform the design and engineering of SI-based robotic systems. It explores the intersection of SI and ST through reflective concept-level analysis, identifying the key similarities, differences, and potential synergies of these approaches. Bridging this gap could enable more adaptive and context-aware solutions for swarm robotics and its control systems. By combining the operational strengths of SI with the analytical depth of ST, we propose a more systemic approach to the development and management of complex robotic solutions.

2. Major Similarities of Swarm Intelligence and Systems Thinking

The first obvious similarity between SI and ST is in their shared focus on understanding complex systems' behaviour. Both approaches also focus on the interactions and relationships between the system's components (e.g., agents) instead of only on its individual components per se. In detail, SI has at least the following main properties that are consistent also with the fundamental ideas and principles in ST (references in brackets):

- **Holistic perspective**: The entity under analysis or design is considered as a whole in both approaches. The interactions between the parts of the entity are as important as the parts themselves (for SI, see, e.g., Hasbach and Bennewitz, 2022; for ST, see, e.g., Senge, 1990).
- **Self-organization**: Both approaches focus on the interconnected units of the system that have some degree of self-organizing behaviour (for SI: Garnier et al., 2007; Kennedy and Eberhart, 2001; Bonabeau et al., 1999; for ST: Jung, 2020). Therefore, a system, such as an ant or a designed robot swarm, adapts and self-organizes to maintain stability and functionality in an uncertain and variable context (e.g., in response to perturbations).
- **Dynamic complexity**: Both approaches acknowledge the dynamic nature of systems and their need to adapt and evolve. In specific, both focus particularly on dynamic complexity via continuous change and adaptation within the system over time (SI: Priyadarshi and Kumar, 2025; ST: Schwaninger, 2020). Adaptation and evolution are temporal processes and any interconnected multi-agent composition that has these properties can be considered to be a complex system (Abbott and Hadžikadić, 2017).
- **Adaptive behaviour as a response**: With SI, a swarm responds to a change in its environment or in its internal conditions (Altshuler, 2023). Also ST emphasizes the importance of understanding how a system adapts and self-organizes in response to perturbations, as well as how it maintains stability and functionality in the face of uncertainty and variability (Abbott and Hadžikadić, 2017).

There are some similar – yet nuanced – key concepts in both approaches that are presented in detail in the next subchapters.

2.1 Adaptation and Learning

A system learns over time that which are the successful adaptations to different situations. There are, however, subtle differences in the conceptual tone of what adaptation and learning means in the context of SI and ST. For bio-inspired SI-based robot swarms, the agents are often framed through mechanisms that allow them to adapt in interaction with the environment and internal conditions. A bio-inspired robot swarm, therefore, is a superorganism that "learns" rather differently in comparison to a single robot with higher processing abilities. In contrast to individual agent learning (see, e.g., Garnier et al. 2007), when collectively intelligent animals and insects learn, they do not learn a "correct" sequence of actions. Instead, an ant colony determines the most beneficial direction between the nest and the food source by the pheromone secreted and sensed by individual ants (Greene and Gordon, 2007). The pheromone that ensures signal reinforcement also allows the recruitment of peers. The colony thus "learns" the shortest path through positive amplifying feedback (Gordon, 2010), while the "parameter values" governing agent behaviour remain the same.

Similarly, in systems thinking, adaptation and evolution are temporal processes, but the complex system is constituted by any interconnected multi-agent composition, not only swarms (Abbott and Hadžikadić, 2017). In brief, both approaches value learning and adaptation as essential for understanding and managing a complex system effectively (for SI: Kennedy and Eberhart, 2001; for ST: Abbott and Hadžikadić, 2017), albeit from a bit different angle. While SI is invested in the pragmatic survival of the swarm and its agents as part of its local environment (Garnier et al., 2007), ST highlights that understanding and managing a system requires attention specifically to how its socio-technical agents interact and evolve over (typically long periods of) time.

2.2 Nonlinear Dynamics Through Interconnectedness and Interdependence

A further similarity with a slightly different tone in SI and ST is their focus on interconnectedness and relationships of the agents in the system. Both recognize the importance of understanding the system's interactions. In SI, a swarm consists of individual agents that interact with their environment (globally) and with each other (locally), making them highly interdependent (Jevtić, 2011). In other words, each agent's behaviour can influence and can be influenced by the actions of other agents. On the one hand, this leads to behavioural patterns of the swarm as a whole. On the other hand, the behaviour of swarms is often characterized by nonlinear dynamics (Rosenfeld, 2015), where minor changes in individual actions can lead to significant effects on the overall swarm behaviour. This nonlinearity can result in very unexpected behaviours and outcomes.

Similarly, ST recognizes interconnectedness and interdependence as key elements of a system, and considering possible unforeseen repercussions of operations over time inside a system is a key focus in ST. For example, Beerel (2009) states that cause-and-effect linear mental models do not serve well in a system-interconnected world. Consequently, modifications to a single component of the system may have major unintended consequences, which take time to manifest in the wider scale.

In conclusion, both SI and ST recognize the potential for so-called “ripple effects” through small behaviour of one agent, or even a slight change of a parameter value of the units of a drone swarm. In practice, a minor design change (e.g., a parameter value change by 1 digit) to the swarm units can offset the swarm behaviour to an entirely different macro-level pattern. Therefore, careful attention and often statistical analysis of several simulation runs are needed in the engineering of drone swarms for precise parameter value determination.

2.3 Feedback Loops and Opportunity for Human Intervention

Both SI and ST emphasize the role of feedback loops in shaping system behaviour and adaptation. Swarms self-organize through feedback loops, where the actions of individual agents produce effects that influence the behaviour of other agents. With ants, for instance, the feedback response is provided by the chemical pheromone signals (Gordon, 2010). In contrast, in a bird flock, the physical movement of one bird triggers a response in neighbouring birds, leading to coordinated movement patterns (Garnier et al., 2007). The diverse characteristics of the related feedback loops contribute to the varying forms of self-organization and adaptive behaviour observed in both biological and artificial swarms (Hasbach and Bennewitz, 2022).

Similarly, in ST, understanding feedback loops is fundamental to analysing system behaviour, identifying leverage points, and predicting outcomes. In short, feedback loops show how the output of a system's action affects its future input, creating a cycle of influence. ST recognizes the nonlinearity inherent in systems and emphasizes especially the need to consider the complex interactions and feedback mechanisms that drive system dynamics (Liu and Barabási, 2023).

As a result for man-made swarms, ST illustrates an opportunity to design interventions as feedback, for instance, from a human operator affecting the swarm’s behaviour while observing it and seeing a need to affect its behaviour. This intervention typically comes through stigmergy-based or other indirect coordination approach (Saffre et al., 2021). In these types of approaches, the local environment is changed (e.g., via “virtual pheromone”), instead of attempting to change the agents’ properties, or to change some global rule in the environment.

2.4 Boundaries and Context

Boundaries impact the understanding and analysis of a system by defining what is contained within and what is outside of it (e.g., Meadows, 1999; Zhang and Ahmed, 2020). Context means the specific environmental, organizational, temporal, or stakeholder-related conditions in which a system operates (Sturmberg and Martin 2024). As swarms consist of multiple agents that are in constant interaction with their environment, the boundary of a swarm may be sometimes hard to define. With biological swarms, the boundary is constituted by each individual insect or animal in their natural environment. In contrast, human swarms constantly renegotiate the immediate physical boundaries of their environment, but also the social, cultural, or technological context that may influence their swarm behaviour (Ylisiurua 2024). In the case of drone swarms (Gumahada and Collins, 2024), the boundary can be constituted by parameter values like distance to other drones, or the swarm’s context such as an urban flight environment.
Also ST highlights the boundaries and context within which a system operates, taking into account the limitations, constraints, and the viewpoints from which the system is seen (Midgley, 2000). In ST, the context shapes crucially how system boundaries are drawn, how feedback loops function, and how interactions among components are interpreted. The context frames both the external environment and the internal dynamics that influence system behaviour (Zhang and Ahmed, 2020).

For drone swarm design, these observations mean that the boundaries and context are to be carefully considered in the design and operation of a swarm. For instance, understanding the boundaries of the swarm is essential for analysing and predicting swarm dynamics accurately. Furthermore, a swarm solution working effectively in one context might be obsolete in another. The actual planned context needs to be therefore clear already in the beginning phase of engineering a drone swarm solution and respected also in the operation of that swarm.

2.5 Emergence

In SI, a swarm’s collective properties, such as strategies and behavioural patterns emerge from the interactions between individual agents and their environment. These emergent properties can include complex patterns of: I) movement, II) coordination, and III) decision-making that are not present at the level of individual agents but arise from the collective (Ganapathy et al. 2025).

Similarly in ST, the emergent properties of a system result from the interactions and relationships within the system (Gharajedaghi, 2011). Furthermore, ST recognizes that the behaviour of the entire system cannot be predicted based only on the behaviour of its constituent parts. ST thus also acknowledges the importance of understanding and analysing emergent properties to fully capture the system’s behaviour.

The main shade of difference of SI to ST here is that swarms emerge typically from participating agents that are structurally remarkably simple and that have a shared set of rules they follow. In that sense, the agents and their appearance or way of being constitutes the boundary between the swarm and its environment. In contrast, a system in ST is more generic and can consist of different types of entities at different level of organization, that share only a few properties. Consequently, the boundary of an observed system in ST is less clear and chosen from the observer’s point of view.

In conclusion, highlighting the opportunity of emergence and designing it in drone systems is a key factor for successful solutions. For example, the performance of a drone swarm is likely to suffer temporarily from an inability to react to a new environment with a property salient to the swarm success, such as an emergent need to learn to perform in snow when the agents are trained to work in a desert. A goal-oriented swarm optimizing its fitness function should therefore learn to navigate in the unfamiliar environment.

2.6 Summary of Major Similarities

In brief, both SI and ST highlight the importance of the interactions and relationships of the actors within the system in causing non-linear phenomena. Table 1 presents their major similarities based on the previous reflections in this section.

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Feature	Similarities between SI and ST
Holistic perspective	Considering the system as a whole, which is more than the sum of its parts.
Self-organization	Emphasizing the interconnectedness of the system, resulting in self-organized behaviour on the collective level.
Dynamic complexity	Acknowledging the system's dynamism and tendency to change over time.
Adaption and learning	Emphasizing how systems can adapt and maintain stability in various uncertain circumstances.
Nonlinear dynamics through interconnectedness and interdependence	Recognizing the interactions and the relationships between the parts of the system, and the resulting potential for nonlinear dynamics.
Feedback loops and opportunity for human intervention	Emphasizing the role of feedback loops in different parts of the system in shaping its collective-level behaviour, opening the potential for unintended consequences but also the opportunity to control the system through deliberate human interventions.
Boundaries and context	Considering both the boundaries and context within which a system operates.
Emergence	Acknowledging the emergent properties arising from the interactions of the parts within the system.

Table 1. Summary of major similarities of SI and ST.

3. Major Differences Between Swarm Intelligence and Systems Thinking

The differences between SI and ST arise, for instance, from the fact that they explain diverse phenomena from different standpoints. SI concentrates on the decentralized emergent behaviour of natural or artificial swarms, whereas ST takes a broader top-down approach to comprehending complex systems. Furthermore, while SI typically focuses on algorithms and artificial intelligence (AI), ST is more about comprehension and optimization. In detail, SI and ST differ from each other in the fundamental ideas described in the following subchapters.

3.1 Level of Hierarchy

One prominent distinction between SI and ST is the depth of hierarchy levels in them. In ST, interventions are typically conducted top-down via centralized control, a higher-level structure that oversees and adjusts the behaviour of the system and its subsystems when they deviate from the desired outcomes. For example, Senge (1990) emphasizes the role of systemic structures and mental models in shaping system behaviour and highlights the importance of identifying leverage points for intervention. These leverage points are typically located at high levels of abstraction and control in the system.

In contrast, the decentralized management of individual agents inside the swarm is the foundation of SI. The group as a whole is not under the direct and explicit control of any single actor. Consequently, the different members of the swarm are relatively equal. This does not, however, mean that there cannot be different roles for the agents within the swarm. Rather, in a typical swarming scenario, each agent in the swarm communicates only with its neighbours and abides some rule set, reacting to local observations.

3.2 Top-down vs. Bottom-up Approach

As discussed above, a major difference between ST and agent-based models is the utilized top-down and bottom-up approaches. ST models usually take a top-down approach, which also automatically gives hierarchy (Mingers and White, 2010), whereas with SI groups of individual agents typically take a bottom-up approach in which the dynamics emerge from the interactions of the swarm's agents (Khare et al., 2023).

A key aspect to consider here is that the behaviour of the swarm is the result of individual decisions and actions (bottom-up), but it does not mean that such behaviour wasn't the target of the process that led to the selection of the decision rules applied on the individual level, whether this process is biological evolution or deliberate design. In other words, a large part of SI design consists in studying systemic properties of, for instance, possible rulesets, mechanisms, and parameter values to identify those capable and sufficient to foster the emergence of the desired global behaviour. These types of bottom-up systems are also very much capable of responding to microscopic events: that is the exact basis of chaos theory (cf. "butterfly effect"; see, e.g., Savi, 2023).

Top-down ST-informed approaches for drone swarm operations could include the human making interventions to the functioning of the swarm. ST may inform especially the development of the operational concept of the socio-technical system for swarm operations in real-life contexts and scenarios.

3.3 Mental Models

Mental models are a key element in ST (Zhang and Ahmed, 2020): they are internal representations that individuals or groups have about how a system works. These models influence the way people, for instance, see situations, evaluate information, and make decisions. They do not remain static; rather, they change with experience, learning, and reflection.

Oftentimes the swarming behaviour in a group of agents capable of higher-level thinking is the result of interactions in which their more "advanced" cognitive abilities or mental models play no part. Human crowd behaviour is a good example of this phenomenon: for instance, the flow of people leaving a crowded metro station is very "swarm-like", because it is governed by remarkably simple interaction between the individuals (e.g., collision avoidance).

Although in agent-based models (Salgado and Gilbert, 2013), such as SI, mental models are not explicitly in focus, they can be inherently included in the evolutionary soundness criteria or in the mind of the designer of the swarm. For instance, at least the swarm designer's mental model has to be quite consistent with its human operator's mental model of the swarm. Therefore, mental models of the swarms' human designer and operator are worth evaluating from the systems perspective in order to optimize the joint cognitive system (Hollnagel and Woods, 2005) of the human-swarm entity.

3.4 Approach to Resilience

Although both SI and ST approaches emphasize the system's resilient adaptation to the prevailing circumstances, they have a different take on how this is achieved. With swarms, for instance, if one member of the swarm is lost, the others can step in and compensate for the loss. Systems using SI frequently show resilience in the face of disruptions or errors (Bari et al., 2023). Because of the swarm's decentralized control, restoring actions are spread across the swarm, which allows adjusting to shifting circumstances without appreciably affecting the system's overall performance (Stolfi and Danoy, 2025).

However, in ST, a change in one part of the system can be also seen to result in drastic changes to the entire system. Especially, in hierarchical top-level models of ST even the smallest change at the top can change the whole behaviour (Meadows, 1999) – which is quite different to agent-based SI models. With swarms, small change affects a rule applied by all agents instead of a single unit and because the nonlinear nature of complex systems leveraging feedback loops means that changing a parameter value can push the artificial system as a whole over a threshold.

3.5 Nature of Dynamics

Both SI and ST consider spatio-temporal dynamics. However, SI often focuses more on the spatial dynamics (as is done, e.g., with drone swarming models; see Saffre et al., 2022), while ST has a more temporal dynamics focus. Especially of interest in ST are the long-term wider effects on system behaviour, reactions to external factors, delays, and feedback over time (see, e.g., Zhang and Ahmed, 2020).

3.6 Level of Abstraction

SI-based swarm models operate at a level of agents and their interactions. However, abstract mathematical modelling is applied in order to investigate the behaviour of the swarm as a whole. This forms the basis for statistical predictability for swarm behaviour. The statistical modelling outcomes help to understand phenomena such as emergence, self-organization, and decentralized decision-making, and for including such phenomena in an artificial swarm's system design. For example, models may predict that a swarm will end up in a certain system state based on stability analysis, although it will usually not be possible to determine how long the process will take. Alternatively, it may be possible to predict what fraction of a time a swarm will spend in each of the possible states.

In contrast, ST models function at a higher degree of abstraction, emphasizing aggregate behaviours and system-wide dynamics (Strijbos 2010). They try to capture the system's overall behaviour by focusing on a small number of imagined agents (Sterman, 2000). Furthermore, ST models typically aim to provide multiple abstraction levels to the system by utilizing various perspectives in the analysis of a system.

3.7 Levels of Analysis

Agents of a swarm often have rather limited ways of interacting with their environment. Consequently, their perspectives may be limited and local. However, taking a multi-level perspective with a swarm allows for a comprehensive understanding of the swarm system, its behaviour, dynamics, and interactions between different levels such as units, sub-swarm, entire swarm, and even swarm of swarms levels. A related example from the is provided by Bjurling et al. (2020) with their various proposed levels of control for the human operator(s) of the swarm.

ST specifically promotes considering the opinions of many stakeholders at various hierarchy levels (see, e.g., Sturmberg and Martin, 2024). It aims to analyse systems at multiple levels of abstraction, from individual elements of the system to its collective dynamics. These levels can be divided, for example, to micro- (e.g., a stakeholder's decision), meso- (e.g., team communication), macro- (e.g., national healthcare system), and meta-levels (e.g., multi-national governance models). In ST, understanding systems' behaviour and dynamics more thoroughly is made possible by analysing them at several levels and integrating various stakeholder views into the system model. ST also encourages moving fluidly between the levels to understand how local actions influence broader dynamics and vice versa (Cox, 2024). Interventions in ST are usually a feature of their higher-level structure: when the lower-level mechanisms are moving the system to a direction that is not wanted, the higher hierarchy can intervene and directly change the course. An analogue of this could be a control system in an industrial environment. This type of control is more direct compared to SI approaches.

3.8 Summary of Major Differences

Based on the previous reflections in this chapter, the major differences between SI and ST are summarized in Table 2.

Feature	Differences between SI and ST
Focus	SI explores emergent behaviours in decentralized systems using algorithms, while ST adopts a broader, often top-down view of complex systems with an emphasis on human-led control and optimization.
Level of hierarchy	SI is decentralized, while ST often involves centralized hierarchical control.
Bottom-up vs. top-down approach	SI uses bottom-up organization (on the micro level), while ST usually has a top-down approach (on the macro level).
Mental models	SI focuses on evolutionary soundness, while ST examines people's mental models of the system specifically.
Approach to resilience	SI emphasizes resilience through redundancy, while ST considers the impact of changes on the entire system.
Nature of dynamics	SI focuses more on spatial dynamics, while ST focuses more on temporal dynamics.
Level of abstraction	SI models operate at a detailed level to simulate individual interactions and enable statistical predictions of emergent behaviour, while ST models abstract these details to focus on aggregate dynamics and system-wide feedback.
Levels of Analysis	SI benefits from observing interactions across different levels, while ST systematically integrates perspectives across various levels to understand and influence system behaviour.

Table 2. Summary of major differences between SI and ST.

4. Seeking Common Ground to Gain Inspiration for the Engineering of Swarm Robotics Solutions

Next, we focus on how SI and ST could come closer together as disciplines by seeking and suggesting areas for common ground with examples for the engineering of drone swarm solutions.

4.1 Common Ground for Adaptation

Adaptation on a general level should be understood as a response to the system's environment or internal conditions. Adaptation is often framed as passive, as if the environment causes pressure on the system while it passively adapts to this pressure. If there are many other possibilities than just mere survival, the system may orientate to an otherwise preferred direction or even develop its new goal on the go. In the contexts of drone swarms, their goal orientation is probably the norm. However, another type of adaptation could be described as "playful orientation" (Ylisiurua, 2024). Certain kind of innovation activity is non-goal oriented and playful, such as when a new technology is tried out for fun. Arguably, current generative AI solutions are used in this way, as users try out what generative AI can actually do and what are its limits.

We suggest that in the design of SI for drone swarms, this type of "playful experimentation" might be fruitful. Unpredictable microscopic deviation from the initial mission plan is part of the approach. This trait is what gives drone swarms their adaptability and resilience compared to directed, more traditional command and control approaches. Nevertheless, this "tuneable noise" is not synonymous with macroscopic unpredictability: if the parameter values are right, for example, a simulated swarm of ants will find the shortest path between the nest and the food source (eventually). Similarly, by using particle swarm optimization (PSO) type of dynamics, one can effectively control the general direction of movement of the swarm, but not the precise trajectory of individual units, which will keep "messing around": this is how they are able to collectively discover new points of interests that were unknown at the time of the mission planning. It also makes it difficult to anticipate precisely what the swarm is going to do from moment to moment, which is a key advantage in many situations. For example, in a search context, it is easy to avoid a detection by a squad of agents following a lawnmower pattern, but hard to do so when they exhibit a swarming behaviour with some inconsistencies.

4.2 Common Ground for Bottom-Up and Top-Down Approaches

The top-down and bottom-up division discussed earlier is a very general-level approach that dismisses the meeting ground and the tensions between the two. To think more towards this direction, consider the following examples. In biology, "a shore" is the boundary area where sea and land meet and form a combination. In economics, meso-level is assessed between the macro and micro economy (see, e.g., Mazzoni, 2024). Similarly, in drone system design, the meso-level boundary appears as an area where the top-down and bottom-up meet and create an emergent structure. For example, a boundary meso-level area may develop between two groups of drone operators from different organizations. In the case of programming robotic swarms where a macro-level operation emerges from the micro-level logic, if one would like to take that operation to a certain direction, it can mean coding a new role into the swarm. However, this role would not be higher in the hierarchy and, for example, "stronger" than others in terms of functions and characteristics, but rather, complementary.

4.3 Common Ground for Feedback Loops and Interventions

As recognized earlier, interconnectedness and interdependence of a system's agents result in feedback loops where members of the swarm form, exchange and interpret messages with each other. In a swarm, these range from awareness of their own state, sensory perceptions of the environment such as vision, to their relative position in the swarm such as the safety distance, and to their relationship to the environment such as flight altitude. In ST, explicit coordination (e.g., human interventions) is an additional feedback feature of a system. With swarms, so-called second-level interventions can also happen where the swarm itself, on its own initiative, starts to act differently for some reason. Since something emerges from the swarm's actions (boundary, structure or something else), that emerged fact can be locally important, such as detecting a local seashore or fire front in case of a drone swarm. However, it might also be possible that the emerged perceptions can be useful in other situations, such as learning to recognize an animal in the forest.

Concurrently, this learning applies differently in different drone swarms' contexts. In agent-based simulations, such perceptions and rules are coded for reliable in silico agents, and consistent behaviour can be expected. In contrast, if a real-life drone unit fails to follow a swarming rule, it is considered an error and is often caused by a mechanical malfunction. However, the rule design could take more inspiration from the biological world. A biological agent (person, ant, fish, bird) not only learns to modify their rule-based strategies but also applies them variably in different situations. As an example, in designed human swarm situations, like traffic, internalized traffic rules and external traffic signs guide the drivers. However, even traffic rules are somewhat flexible, because there can be weather conditions, miscreant drivers, and emergency situations, which agents assess differently. Consequently, all rule deviations are not errors, nor are they random ways of reacting. Nevertheless, the deviations may have non-linear effects. In the context of machines, one could thus perhaps say that such quirks are features, not bugs of the system, and it's good to understand them. This is especially salient because, in a real-life robotic swarm, there can be several devices made in different manufacturing facilities and of different generations. These may work technically differently and interpret each other's behaviour in varying ways, which one should be able to take into account when designing their collaboration and control.

5. Discussion

While SI and ST have distinct focuses and methodologies, they share common principles related to, for example, understanding complexity, emergence, and adaptation within systems. This reflective paper suggests that combining SI (that is traditionally used in swarm robotics; see, e.g., Cheraghi et al., 2021) and ST (that is typically used in human systems modelling; see, e.g., Sterman, 2000) can lead to novel solutions in the development of drone swarms. For instance, by deeply understanding and utilizing the obvious common ideas of emergence, advancement of holistic design, and definition of suitable boundaries for the system, drone swarm researchers and operators can gain insights into the underlying mechanisms driving the system's behaviour and design effective solutions for various applications in the future. Furthermore, by bridging the differences between the disciplines, for example, with conceptual analysis type of approach utilised in this paper, we can gain inspiration from ST to the design of, for example, robotic drone swarms. Finding a common ground between these approaches would significantly benefit artificial swarm system (e.g., drone swarm) design.

The paper also details some less obvious key areas where common ground between SI and ST is sought, along with suitable practical-level examples. Table 3 summarizes some of our discovered implications and advice on these chosen areas for the design of drone swarms. By applying ST principles to the study of swarms, the researchers, designers and engineers of drone swarms can gain insights into the underlying mechanisms driving swarm behaviour, predict their dynamics, and potentially design or control robotic swarm systems. Utilizing ST may allow to study swarms not as isolated entities, but as intricate patterns of relationships. Based on our analysis, the

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following preliminary implications can be drawn on how to utilize ST to improve the design of artificial swarms:

- Understand emergence: Study how local rules lead to global patterns. Analyse in detail the emergent properties, such as self-organization, synchronization, and adaptation.
- Advance holistic design: Design swarm behaviours that align with the whole system's purpose (e.g., exploration, surveillance, etc in case of drone swarms).
- Test for robustness: Study the swarm's responses to disturbances and evaluate its resilience via its adaptation patterns both with simulations and real-world tests.
- Define suitable boundaries: Define the swarm's behavioural boundaries clearly and consider the context (e.g., the environment) in detail in this process.

Common Ground	Implications	Advice
Adaptation	*Goal-oriented* adaptation responds to environmental pressures with specific objectives, while *playful* adaptation involves experimentation without predefined goals.	Experiment with both goal-oriented and playful approaches in swarm design to enhance the solution's adaptability and resilience. Balance-directed approaches with tuneable noise for optimal performance.
Bottom-up and top-down approaches	The meso-level is where the top-down and bottom-up approaches meet, creating tensions and structures. This level' is crucial for optimal emergent structures and practices.	In design work, focus also on the meso-level to understand and manage the interactions between top-down (macro-level) and bottom-up (micro-level) processes.
Feedback Loops and Interven-tions	Second-level interventions occur when the swarm acts differently on its own initiative, leading to emergent structures or boundaries. These can be locally important and have broader implications.	Enhance communication and feedback mechanisms within the swarm to improve collective decision-making. Monitor and analyse emergent behaviours within the swarm to identify functional patterns and structures. Use these insights to inform robotic swarm designs and related interventions.

Table 3. Some implications and advice for the common ground sought between SI and ST to improve the design of swarms.

6. Conclusions

Based on earlier research, this paper analysed the key characteristics of SI and compared them with the core concepts of ST. The paper suggested that novel solutions for complex systems, such as drone swarms, can be developed by integrating high-level principles from both fields. A general-level benefit of the ST approach for the design of swarming systems is the more systemic approach to considering the swarm as a whole and predicting its potential transitions already in the design phase.
Future work in this domain includes practical-level experimentation and empirical studies using both approaches. A key aspect in this context is to study the same phenomenon both with SI and ST simulations, from which the results would then be compared and a unified methodological approach sought. Overall, a common ground sought between the two approaches can lead to improved control, amplified swarm behaviours, and increased adaptability of the developed solutions. By applying certain top-down ST principles to the study of bio-inspired bottom-up SI solutions, researchers, engineers and operators of drone swarms can gain insights into the underlying mechanisms driving the swarm's behaviour, predict its dynamics, and design the systems better for various application fields, such as geomatics, environmental monitoring, and firefighting. This paper aims to serve as the first step in considering both approaches in an integrated manner.

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