

Software Engineering for Collective Cyber-Physical Ecosystems

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ABSTRACT

Today's distributed and pervasive computing addresses large-scale cyber-physical ecosystems, characterised by dense and large networks of devices capable of computation, communication and interaction with the environment and people. While most research focusses on treating these systems as "composites" (i.e., heterogeneous functional complexes), recent developments in fields such as self-organising systems and swarm robotics have opened up a complementary perspective: treating systems as "collectives" (i.e., uniform, collaborative, and self-organising groups of entities). This article explores the motivations, state of the art, and implications of this "collective computing paradigm" in software engineering, discusses its peculiar challenges, and outlines a path for future research, touching on aspects such as macroprogramming, collective intelligence, self-adaptive middleware, learning, synthesis and experimentation of collective behaviour.

CCS CONCEPTS

- Software and its engineering → Software development methods; System description languages; Software organization and properties;
- Human-centered computing → Collaborative and social computing;
- Computing methodologies;

KEYWORDS

cyber-physical ecosystems, collective adaptive systems, swarm intelligence, macroprogramming, edge-cloud continuum

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1 INTRODUCTION

Technological advances in computing systems and networking and trends like pervasive computing [41] and the Internet of Things (IoT) [81], promote an increasing digitalisation of our world, which is being filled with interconnected computing devices supporting a variety of services and applications. In this work, we are concerned with the general high-level problem of how to unleash the potential of *large-scale distributed systems* [130] by proper engineering of the software managing them or driving their overall behaviour.

Specifically, in this paper, we focus on *collective cyber-physical ecosystems* (CCPEs). By *cyber-physical*, we indicate that systems consist of *situated computing* devices able to sense and/or act in the physical environment; without neglecting that systems may also comprise non-situated and infrastructural devices (e.g., edge servers, the cloud, etc.). By *ecosystem*, we mean that devices *live* and interact with each other within the environment, functioning as an "ecological unit", i.e., interacting to provide functionalities in a long-term equilibrium; in particular, we consider both short- and long-lived tasks which may require cooperation and must adapt to perturbations. By *collective*, we mean that multiple devices can be regarded as a whole, solving distributed tasks through *computational collective intelligence* (CCI) [30, 65, 86]. Examples of CCPEs include robotic swarms [23], smart cities [47], edge-cloud infrastructures [142], and crowds of people with wearables [53].

In the research landscape of *software engineering* (SE) for CCPEs, mainstream approaches – like (micro-)services, programming frameworks, and artificial intelligence – are typically applied under a view of "*systems as composites*"; in this view, a system is built as the *integration* of *heterogeneous* components, which can be engineered largely independently of the others. Recently, results from niches of several research threads – like collective adaptive systems [97], self-adaptive software [136], macro-programming [31, 74], and swarm robotics [23] – promoted the complementary view of "*systems as collectives*". In this view, a system is engineered "as a whole", adopting (declarative) abstractions, tools, and methods suitable to coordinating groups of interacting devices, letting their CCI emerge.

In this paper, we address the impact of adopting a collective stance in software engineering for large-scale distributed systems,

considering CCPEs as main target and artificial CCI as main goal. To this end, we provide a review of the state of the art on CCPE engineering, emphasising the different approaches involved and then highlight key challenges that we expect may contribute to the research and development of SE.

The rest of the manuscript is structured as follows. Section 2 details on the motivation for the emerging of the “system as collectives” perspective in software engineering. Section 3 reports on the state of the art on CCPE engineering, and its main themes. Then, in Section 4, we highlight relevant challenges fostering research in software engineering for CCPEs. Finally, Section 5 offers a wrap-up.

2 SYSTEMS AS COLLECTIVES

In this section, we detail on the motivation for a collective viewpoint in software engineering for large-scale distributed ecosystems.

2.1 Context and high-level challenges

Engineering pervasive and cyber-physical (eco-)systems is challenging [16, 24]. Indeed, many challenges have to be addressed, including the implications of *distribution* (cf., lack of global clock, multiple administrative domains, dynamic topologies, latency and cost of communication, failure, inconsistency, security) [124], the integration of *discrete* and *continuous* dynamics [35], the implications of *large scale* deployments [100], and the *design of collaborative logic* (cf. Section 3). For instance, addressing large scale typically requires the design of *decentralised* solutions to avoid *single points of failure* and *performance bottlenecks*. To deal with different requirements in terms of latency, cost, and performance, deployments often target multiple layers of the *edge-cloud continuum (ECC)* [142]. Also, since large-scale deployments complicate *maintenance*, the design should involve *autonomic capabilities* [77], endowing systems with some *adaptation* or *self-* properties* (e.g., self-organisation [58, 147], self-reconfiguration [42], self-improvement and self-integration [17]).

2.2 SE approaches for distributed systems

The majority of current solutions for distributed software design leverage (*micro*-)*services* [49], stream processing [46], or *event-driven* platforms [38]. These techniques are suitable also for CCPEs, though challenges related to heterogeneity, deployment, efficiency, integration, and security are hindering their adoption in specific domains like manufacturing [142]. General approaches to *service composition* [79, 104] include *orchestration* by (possibly multiple) centralised entities [131] or *choreographies* for decentralised interaction protocols [90]. An interesting related SE practice is the use of *architectural description languages* [103] describing the components and constraints of an entire distributed system, and its specification in a single codebase—cf. *multi-tier programming* [135].

Concerning *self-adaptive software systems* [136], there are multiple classes of self-adaptation approaches. The *reference model* for self-adaptive systems [77] distinguishes between the *managing* and the *managed* system, and generally organises a feedback loop around the *MAPE-K* (*Monitor, Analyse, Plan, Execute - Knowledge*) components within the managing system. Upon this basis, *architecture-based* approaches emphasise runtime reasoning about architectural models; *requirements-based* approaches emphasise

the specification of requirements, often relaxed to deal with uncertainty, and meta-requirements about the self-adaptation itself; *control-based* approaches leverage control theory to formally design and analyse the self-adaptation logic; and *learning-based* approaches exploit machine learning to synthesise accurate models and plans.

In *decentralised* self-adaptive systems, adaptation control is distributed among different components equipped with feedback loops. This is similar but often distinguished from *self-organising systems* [20, 147], which generally consist of a larger number of simpler components that seek system goals by repeated local interaction. Engineering self-organisation is a matter of identifying mechanisms and techniques to *steer or guide the emergent behaviour* of groups of interacting agents [114, 147].

2.3 From composites to collectives

At this point, we deem useful to distinguish between two related but distinct kinds of possible target *systems*, where a system is generally meant, coherently with systems theories [89], as a *plurality* of entities considered together within an arbitrary boundary. In particular, we are inspired by the ontological distinction between composites and collectives in Masolo et al. [88]. A *composite*, a.k.a. an assembly or complex, consists of different kinds of components, thus exhibiting substantial *heterogeneity*, organised in a recursively decomposable functional structure with multiple roles. A distinct but related and non-disjoint notion is that of a *collective*, which is a more *homogeneous* set of entities related by some non-transitive *membership* relationship. Roughly, then, examples of composites include the distributed software modules that collaboratively operate a manufacturing machine, or a team of agents with significantly different capabilities interacting following a complex protocol; whereas a swarm of similar robots, a cluster, or a sensor network are exemplars of collectives. Research in fields such as swarm robotics [23], collective adaptive systems [97], and artificial life [23, 58] shows peculiar traits of collectives, motivating new approaches to their engineering. Abowd [2] refers to *collective computing* as the fourth revolution after the mainframe, personal, and ubiquitous computing revolutions. Indeed, the *collective intelligence* [65, 120] emerging from the collaboration of humans and technologies has the potential to overcome important societal challenges [121]. Even when humans are not an active part of a solution, the engineering of *artificial collectives* [30] can contribute by improving existing applications (e.g., through increased autonomy and resilience), unlocking novel ones (cf. *drone crowdsourcing* [10] and *IoT-as-a-Service* [69]), or sustaining the autonomous operation of large ecosystems in smart infrastructures and smart cities [47, 105].

The interest in large-scale CCPEs is mounting. In these systems, besides the local services and tasks (often resulting from *complex networks of collaboration*), there is increasing interest in *global-level services* (e.g., surveillance, waste collection, task allocation, group coordination) and *global-level properties* (e.g., overall energy consumption, system-level resilience). Accordingly, several research efforts are noticing *fundamental gaps in software engineering for these systems* and consequently foster the *collective viewpoint* in system analysis, design, and implementation, with *collectives* and *collective phenomena* [140] as first-class citizens [31, 72, 74, 93]. In the

next sections, we detail on these contributions, further motivating interesting developments and challenges in software engineering.

3 SE FOR CCPEs: OVERVIEW

In this section, we discuss the main issues encountered when engineering CCPEs, and then provide a view of the state of the art.

3.1 Main Themes in SE for CCPEs

3.1.1 Local-to-global and global-to-local mapping problems. When dealing with CCPEs, there are two main issues [15, 30, 129].

The *local-to-global mapping problem*, also known as the *forward* or *prediction problem*, entails determining what will be the global outcome out of an execution of the local behaviours making up the system, for a given set of environment dynamics. Indeed, in the traditional “node-centric” engineering viewpoint, the programmer thinks about how the behaviour of an *individual agent* will affect other agents and its surrounding environment. However, to determine the global or system-level result, the behaviour of other agents and the environment have to be considered as well, resulting in a complex network of causes and effects, often leading to *emergent phenomena*. In emergence, it is difficult to trace the micro-level causes that led to a given macro-level observable. In other words, emergence makes prediction difficult or impossible: the general solution consists of “running the system”, i.e., seeing where the chain of events and the historical contingencies lead the system. This makes *simulation* an invaluable tool for studying and analysing collective behaviour.

The *global-to-local mapping problem*, also known as the *inverse* or *engineering problem*, entails determining, from a global outcome (*target state*), what local behaviours will conduct to it and how. Clearly the two problems are related, as two sides of the same coin.

Other names for these problems and corresponding solutions are also *micro-to-macro* and *macro-to-micro*, respectively [31, 115, 148]. It is relevant to introduce this terminology because several research threads do use these terms, and in our integrative effort we aim at removing fictitious linguistic barriers. Indeed, in multi-agent systems, it is frequent to talk about the micro-level of agent activity and the macro-level of *agent societies/organisations* [115, 141], and the research thread of *macro-programming* [31, 74] is exactly where the forward and inverse problems are addressed by using programming languages. Figure 1 depicts the general idea graphically, where macro-observables are abstracted as functions of the inputs from the individuals and environment, as in [65, 99].

In the traditional “node-centric” engineering viewpoint, there is an implicit global-to-local solution that is limited to the designer’s mind or at the requirements phase. In this paper, we analyze how recent research [15, 23, 31, 72, 74, 92, 97, 106] shows that design can start from the “global” perspective, ideally with declarative definitions that represent the intended global behaviour, then implementing local behaviours by a formal global-to-local mapping technique, and finally going forward for proper testing and validation with a local-to-global mapping technique.

3.1.2 Automatic vs. manual design. Various works in the context of multi-agent systems and swarm robotics suggest that techniques for the design of collective behaviour can be classified in two main categories [23]: automated techniques and manual techniques.

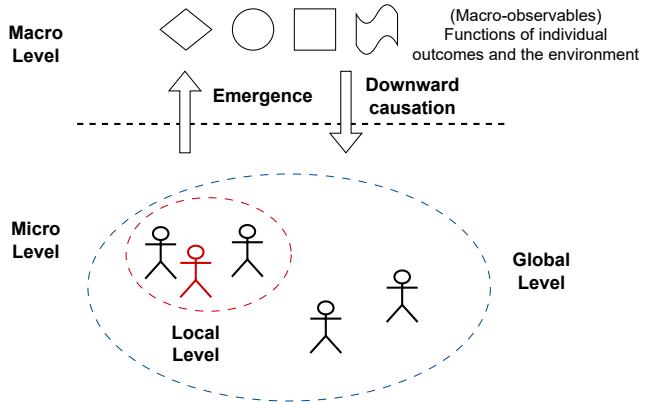


Figure 1: The local/micro and global/macro levels of systems. The shapes at the top are just abstract denotations of macroscopic information obtained by an application-specific, abstracted function of the microscopic data taken from the agents and environment (cf. [59, 65]). The stylised agents are not necessarily people but also artificial autonomous agents.

Automated design methods [26] work at the meta-level of algorithms, defining procedures for learning or synthesis of the control programs driving (the individual agents of) CCPEs. Prominent examples of this family are *evolutionary methods* [127], *multi-agent reinforcement learning* [28], and *program synthesis* [62].

Manual or *behaviour-based* design methods, instead, include the classical programming activity, where the programmer follows trial-and-error processes to craft algorithms using general-purpose or domain-specific languages. When addressing collective behaviour, this is also referred to as *macro-programming* [31] (discussed more deeply in Section 3.2.2).

Note that, being automated design the meta-level application of manual design, these two classes are not necessarily disjoint: indeed, key research opportunities lies in this overlap [6, 7, 37, 144].

3.1.3 Understanding and building “collective intelligence”. Collective intelligence (CI) can be generally intended as the property of groups of individuals behaving in ways that seem intelligent [86]. This definition reuses possible definitions of “intelligence”, typically as a collection of task-specific skills or, in a stronger sense, as a general problem-solving and learning ability [39]. So, a CCPE is intelligent if it is able to solve tasks in a variety of environments, possibly adapting itself to cope with new problems.

Remark that the term “collective intelligence” leads to two main related areas: socio-technical systems [120] and artificial collectives [30]. The former emphasises the complex collaboration of humans and technologies, whereas the latter emphasises the engineering of multi-agent systems consisting primarily of artificial devices. The two research areas are related, and humans are indeed considered in the latter kind of systems as well, but the problems addressed are quite different (roughly, more human-computer interaction on one hand, and more behaviour control design on the other hand). Since socio-technical systems tend to feature increased complexity of agents and heterogeneity, hence leading to composites, in this work we mainly focus on artificial collectives. We explicitly

refer to the interpretation of CI as *computational collective intelligence (CCI)* [30, 123], meaning the intelligence globally exhibited by groups of computing devices.

3.2 State of the Art in SE for CCPEs

It follows a non-exhaustive review of contributions to SE for CCPEs, aiming at illustrating its main problems, methods, and techniques.

3.2.1 Learning/evolving collective behaviour. The automatic approach in CCPEs design has been a focal area for over 20 years, encompassing various fields such as swarm robotics [23], traffic management, and crowd engineering. In this area, two main approaches have been studied: *evolutionary approaches* [127] and *reinforcement learning (RL)* [122]. Both rely heavily on simulation to provide necessary feedback for refining generated controllers. Evolutionary approaches draw inspiration from natural evolution, starting with a set of controllers that evolve based on simulation feedback. The design of a controller is highly dependent on the scenario and desired complexity, using finite state machines [57], neural networks [54], and Boolean networks [22]. The state of the art in this research area is attributed to AuToMoDe [56], a general framework for generating controllers for robot swarms.

In the realm of *collective RL* [80], initial efforts, such as those by COIN [139], focused on bottom-up CCI, aiming to enable multiple agents to learn concurrently via RL. These early efforts evolved towards prioritizing the collective as a primary entity, thus shifting focus to designing individual agent controllers. For instance, a novel model named swarMDP [118] was introduced to simplify the modelling of learning processes for swarm-like systems, characterised by homogeneous entities (same controller) with a partial observability of the environment. This model represents an initial top-down approach, where the controller, possessing a global view, is then distributed into similar controllers for individual robots.

In the state of the art, there are two main strategies. One strategy, aimed at collaborative systems with few agents and exemplified by COMA [55] and MAPPO [149], addresses the individual behaviour of agents that cooperate to achieve collective intelligence. Another strategy, targetting more large-scale systems, let collective behaviour emerge through a uniform controller, akin to swarMDP but leveraging more recent models like mean-field games [145]—this is often known as *many-agent reinforcement learning* [143]. In the *centralised training and decentralised execution* approach [61, 78], controllers are derived from a global perspective and then distributed throughout the system. This methodology simplifies the learning of collective behaviours and allows for the verification of outcomes during simulation.

3.2.2 Macroprogramming. Macroprogramming is the umbrella term that gathers programming solutions for defining and executing the macroscopic behaviour of software systems [31, 74]. The definition is voluntarily broad, since it mostly serves as a basis for integrating and finding commonalities among different solutions for similar problems recurring in disparate domains, from wireless sensor networks [92, 95] and parallel computing [126] to swarm robotics [106] and software-defined networks [75]. So, the real question is not whether a programming solution is an instance of macroprogramming but rather to *what extent it is so* [31].

In particular, certain macro-programming approaches do expose *collective-level abstractions*, and programs can be read as instructions targetting not an individual device, but rather a collective of devices, hence *the computing machine is conceptually the whole distributed system of computers*. Achieving that, often entails some forms of *declarativity* at the language level, a compilation of local programs from the global specification (cf. [135]), and a non-trivial interplay between the local/global programs and the middleware (cf. Section 4.2).

For a detailed picture of the state of the art on macroprogramming, the reader can refer to these two recent surveys [31, 74]. It should be noticed that the surveys do not cover research contributions that are rather focussed on smaller-scale heterogeneous systems, i.e., composites, and hence captured by the related fields of *choreographic programming* [43], *multi-agent oriented programming* [19], *architectural description languages* [85], and *multi-tier programming* [135].

3.2.3 Aggregate Computing. Aggregate computing is a prominent macroprogramming approach for CCPEs [134], developed for more than ten years. We briefly recall its fundamental features: *bio-inspiration, formality, pragmatism, compositionality, deployment-independence*.

Generally speaking, a major general theme in software engineering for CCPEs is finding ways to map scientific theories about natural phenomena to software engineering constructs (e.g., programming abstractions or platforms)—cf. *bio-inspired* mechanisms [51]. In the case of aggregate computing, the mechanism of self-organisation [58] is reflected in the execution model (implemented in the runtime or middleware) of programs written in this paradigm, which assumes that each device computes in repeated asynchronous sense–compute–interact rounds.

The programming paradigm is formally founded on *field calculi* [14], functional core languages for expressing manipulations of *computational fields*: distributed data structures mapping sets of devices to values, hence denoting collective inputs and outputs. This enables deriving guarantees and proofs about programs, e.g. to assess that a collective computation is *self-stabilising* (roughly, eventually converging to the “right” value) [133].

These calculi are implemented by standalone or embedded *domain-specific languages (DSLs)* [134], also providing pragmatic libraries of reusable functions capturing recurrent patterns of collective behaviour. Using these languages and libraries, the programmer defines a single program expressing the whole behaviour of a collective as a *composition* of building blocks.

Then, the program can be deployed on a network of devices, using a simulator or leveraging a proper middleware support on real systems [32]. By distinguishing the logical model of the system from its physical deployment, it is also possible to partition an application into deployable components and hence offload computations across the edge-cloud continuum [32].

3.2.4 Models, Methods, and Tools for CCPEs. A few works provide early contributions addressing (parts of) the development life-cycle for CCPEs, mainly from the research area of collective adaptive systems [97]. Actually, the majority of these, briefly reviewed in the following, lie at the intersection of composites and collectives.

There is a number of contributions about the use of formal methods for the specification and quantitative evaluation of collective adaptive systems [18]. One example is *CARMA (Collective Adaptive Resource-sharing Markovian Agents)* [83], a stochastic process algebra supporting the modelling and verification, through a stochastic simulator, of quantitative properties of collective behaviour like performance, availability, dependability.

Another major source of contributions was the *ASCENS (Autonomic Service-Component ENsembles)* project [137]. This project proposed approaches and formal languages for the specification and analysis of *ensembles*, namely dynamic groups of devices exhibiting complex interactions and working in complex environments [138]. In the *SOTA (State Of The Affairs)* and *GEM (General Ensemble Model)* approach [1], collective behaviour is denoted as a trajectory in a state space where each point denotes a single “state of the affairs” comprising all the information about the ensemble and its environment. Regarding the programming of ensembles, ASCENS features the *SCEL (Service Component Ensemble Language)* [98], a process-algebraic abstract language for specifying behaviour of individual entities, of aggregations of entities, based on *attribute-based communication* [9], and in a way that is parametric to knowledge repositories and adaptation policies.

A related approach to engineering dynamic ensembles is provided by Buccharone et al. [25], based on *domain objects* encapsulating behavioural processes and exporting *process fragments* for refinement and composition. These networks of domain objects (i.e., ensembles) can be modelled using typed graph grammars [68].

A programming framework for hybrid collaborative systems is proposed by Scekic et al. [116]. There, collectives are teams of *peers* (abstracting *humans* and *machines*) performing “collective-based tasks”, e.g. in crowdsourcing settings. The approach, based on the SmartSociety framework [116], provides a Java-based platform and Application Program Interface (API) for the *orchestration* of such hybrid ensembles, supporting *managed* collectives, collective task management, adaptation policies (expressed in terms of changing handlers attached to task transitions), as well as other services for communication and incentive management. The interesting part of the approach is the combination of *collectiveness* (where collectives are the first-class citizens managed by the platform) and *human orchestration*, and the positioning of the contribution roughly half-way between composites and collectives engineering; however the approach is quite ad-hoc and with limited methodological guidance.

There are other approaches similar to SCEL, domain objects, and SmartSociety that share some of their motivation and abstractions, and provide related DSLs and platforms supporting modelling, implementation, and limited forms of verification. These include, e.g., *DEECo (Distributed Emergent Ensembles of Components)* [27].

Generally, any approach like aggregate computing, CARMA, or ASCENS comes with its own toolchain, but there exist also “standalone” tools. One toolkit for reasoning about collective adaptive systems is *Sibilla* [60]. It is a modular framework supporting multiple specification languages (e.g., for interactive objects, population models, and agent-based systems), organised with a three-layer architecture comprising: (i) a back-end supporting modelling, simulation, and analysis; (ii) different front-ends (APIs and shells), and (iii) a runtime system coordinating activities.

3.2.5 Methodologies for CCPEs. The aforementioned SOTA and GEM models promote *goal-oriented* [70] adaptation requirements engineering. However, there are also studies on specific properties of CCPEs or peculiar aspects of their engineering.

In [8], a systematic review is carried out studying how existing approaches deal with *uncertainty* and *adaptation* in CCPEs. Also, a *design guide* is proposed for uncertainty-aware components in CCPEs, highlighting the need of identifying uncertainty sources (e.g., failure, delays, noise, missing information) and “border situations” to feed methods for handling uncertainties (e.g., humans-in-the-loop, reconfiguration, and declarative behaviour) before performing the adaptation decision-making.

Regarding engineering self-organisation and emergence, there exist some ideas and high-level guidelines [99, 108]. For instance, Nöel and Zambonelli [99] contrast with approaches based on micro-level design and rather suggest to focus on the macro-level: *“the global behaviour must emerge, exploiting self-organisation imposes some design constraints and decomposition plays an important role in what can emerge”*. In particular, they delineate two different decomposition strategies: *organisation-based* (by distinguishing roles) and *functionality-based* (by breaking global tasks into global sub-tasks). In the former strategy, literature on multi-agent organisational paradigms is especially relevant [71].

4 SE CHALLENGES FOR CCPEs

In Section 3 we provided an overview of works contributing to the engineering of CCPEs. At their core, there are notations and tools supporting automatic and/or manual approaches helping to bridge the intended global behaviour with the local control program of the agents of the CCPE at hand. The general goal is promoting forms of collective intelligence out of whole networks of devices. The key insight is that several research works [15, 23, 31, 72, 74, 92, 97, 106] witness the need of embracing the collective viewpoint, possibly throughout the software engineering process [97, 137]: cf. requirements expressing system-wide properties [1], models and languages considering groups of entities and values as first-class abstractions [31, 72, 74], verification techniques leveraging model-checking or simulation to assess the emergents [60, 83, 133]. In the following, we highlight gaps in the state of the art, denoting key challenges to be addressed in the context of software engineering of next-generation distributed systems.

4.1 Handling Homogeneity and Heterogeneity

4.1.1 Integrating collectives and composites. A major challenge in engineering CCPEs is the integration of heterogeneous entities into a coherent framework, where the system can be inspected, understood, and designed (or trained) as a single entity (in the spirit of macroprogramming, cf. Section 3.2.2). Macroprogramming approaches, in fact, are particularly well-suited for systems composed of homogeneous entities, where the collective behaviour can be abstracted and reasoned about at a high level of abstraction. Thus far, however, there is a lack of formal and practical methods to deal with heterogeneity from a collective perspective, exploiting the peculiarities of every device without renouncing the benefit of observing and designing the system as whole.

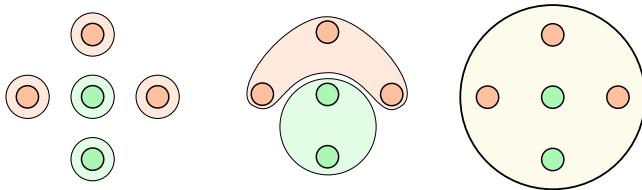


Figure 2: From composites to collectives. In composites (left) every entity composing the system must be observed, understood, and designed/trained individually; communication between entities needs to be modelled explicitly. In collectives (right) all entities are observed, understood, and designed/trained as a single entity; communication is implicit; dealing with the heterogeneity of the single entities is still an active research topic. Hybrid systems (centre) are possible: the system gets partitioned into multiple subsystems, typically capturing homogeneous devices, building a de-facto composite of collectives.

In Figure 2, we provide a graphical representation of the difference between composites and collectives, including also somewhat *hybrid* systems, where the whole composed of heterogeneous devices is partitioned into multiple subsystems based on their internal homogeneity. Although this idea helps with managing complexity, it does not fully exploit the potential of a collective viewpoint over a heterogeneous system. Consider, for instance, a system composed of drones and ground robots: a truly collective approach would be able to form mixed teams with capabilities that can only be achieved by combining the two types of devices (for instance, exploiting the aerial view in specific areas to assist ground robots in navigation and path-finding); while a hybrid approach would partition the system into two homogeneous communicating subsystems, losing the ability to create multiple small independent teams.

Providing means to tame heterogeneity without losing the privileged observation position of the collective has great potential to enable a leap forward in several fields, including swarm robotics [48, 76], the IoT [34, 109], and the edge-cloud continuum [52].

4.1.2 Multi-targeting and software product lines. The theme of heterogeneity, largely impacting on how abstractions can be captured (cf. Section 4.2), has rippling effects on the software development process. In fact, even though the software is designed from a collective perspective, it will have to be executed on possibly very diverse devices, ranging from edge servers and cloud instances to smartphones and wearables to modest microcontrollers and sensors. Although decompositional approaches have been proposed to tackle the problem of some devices being unable to participate in some parts of the collective computation [33], they do not account for the production of multiple versions of the software that can execute on very diverse devices. This problem can be fractioned into two macro sub-problems: (1) producing software *compatible* with different target platforms from a single specification, and (2) customising the specific software configuration considering the final target. The first problem imposes a significant maintenance burden on potential middlewares (as they must be able to run on multiple

platforms), potential external DSLs (as they must be able to generate code for multiple targets), and may severely limit the adoption of internal DSLs (as they are constrained by the platforms targeted by the host language). The latter problem calls for future CCPE-specific software product lines [125], supporting the customisation of the final software in a target-specific fashion.

4.2 Specifying and Running Collectives: DSLs, Middlewares, and Their Interplay

Capturing collectives in a way that is actionable analysts and designers requires appropriate abstractions to be reified. Thus, at some abstraction level, multiple devices must operate as a single one, although in the respect of their possible heterogeneity. Doing so, technically, can be performed in two ways:

- through a middleware, creating a software layer that abstracts the collective as a single entity; or
- through a DSL, capturing the collective behaviour at design time and translating it into executable specifications.

Middlewares are the historically preferred approach to building a shared layer multiple autonomous entities can interact through [87, 107]. Indeed, a middleware is a natural solution, as it provides a shared unified layer, enforcing homogeneity over possibly heterogeneous devices. This strategy has been used in the past for non-distributed system with success: we may ascribe to the “middleware” category all those execution runtimes that could be targeted by multiple programming languages, such as the Java Virtual Machine (JVM) (targeted by Java, Ruby, Scala, Kotlin, Groovy, and many other languages) or the Common Language Runtime (CLR) (targeted by VisualBasic.NET, C#, F#, ...). On the other hand, however, middlewares can be impractical, as they normally require multiple implementations for different platforms, and they impose certain requirements on the underlying systems. In the exemplary case of the JVM (which is akin in other runtimes) the middleware has to be implemented for each supported platform, with each implementation possibly featuring slightly different implementations. We observe that there is a trade-off between complexity and portability: the middleware’s portability will be favoured by minimality; on the other hand, a minimal middleware will hardly provide high-level abstractions suitable for high-complexity systems, thus requiring further layers, each one possibly imposing further restrictions on the underlying platform. For instance, a middleware developed on top of the JVM will not be capable to be executed on devices or runtimes for which a JVM is not available, such as the browser, or low-power wearables.

DSLs come instead with a different set of trade-offs. The idea behind a DSLs is to create new abstractions as part of the language itself, letting the compiler (interpreter) figure out how to translate (execute) the program. DSLs can be realised in two ways: as *standalone* (or *external*) languages [112], or *embedded (internal)* into an existing General-Purpose Language (GPL) [113]. The former approach is more flexible, but it requires more development and maintenance effort, while the latter is constrained by the syntax and semantics of the host GPL, but, in turn, can immediately leverage its compiler/interpreter, its tooling, and feature a much gentler learning curve for designers acquainted with the host GPL; an internal DSL, de facto, is a library designed to exploit the syntactic

features of the host language in such a way that the feeling is akin to using a dedicated language.

The two approaches are not mutually exclusive, rather, they reinforce each other. In fact, at some point, the code written in a DSL will perform communications over a network; and these communications could well be mediated by a middleware. On the other hand, the infrastructural support a middleware provides will be exposed to the designers through an API, which may be expressed, e.g., in form of an internal DSL. In practice, we have a spectrum of possibilities, and understanding the better trade-off from the two extremes of a pure DSL directly calling networking primitives under the hood and a pure middleware driven through a regular API is yet to be investigated. This investigation becomes even more challenging under the consideration that different applications (with different contexts and objectives) developed by different teams (with different expertises) may benefit from different balances, and one specific design will hardly fit well in all conditions. Clear guidance directed to CCPE DSL and middleware providers on the trade-off each design choice brings on the table is yet to be devised.

4.3 Verification and Validation

Static analysis. A first line of defence against bugs, smells, and vulnerabilities is static analysis; however, the adoption of static methods based on model checking is limited by the size, openness, and autonomy of CCPEs [82]. In response, formal methods are being developed to support CCPE-tailored analysis [36, 119]. Further steps are required in this direction, and, from a practitioner's point of view, these research efforts need to be reified into actionable tools (possibly language- or middleware- specific).

Simulation. In distributed systems, testing is a main challenge [110]: executing the software on a single machine (even when software pieces are isolated through Virtual Machines (VMs) or containers) attenuates (or removes altogether) many of the potential issues to be faced at runtime, such as network failures, slowdowns, Content Delivery Network (CDN) updates, and internal Domain Name System (DNS) lookup issues. In the case of CCPEs, the problem is exacerbated by the large scale, which makes it unpractical (when plainly impossible) to test the software on a single machine. The most immediate consequence is that *simulation* becomes a necessity in multiple phases of the software production [4]: fast simulator with a very simplified model of the world can support the developer in the early stages of development; while more detailed simulations, with accurate physics and network models (and much longer time to execute) are needed to support in-depth testing [11]. Capturing different degrees of complexity with a single simulator is a significant challenge [3], we envision that using multiple simulators for different phases of the development could be a viable solution. Orthogonally to scale, the dynamicity of CCPEs, in which violations of the nominal states are generally unpredictable, is a major challenge for simulation [3]: generating critical scenarios automatically is another interesting challenge ahead.

Test Cases: Inputs. CCPEs are made of (possibly very large) groups of computational entities, which require multiple levels of testing, as multiagent systems [40]. We can think of (at least) the following levels: single entity; neighbouring entities; global system. The main

challenges are posed by the third level, since the number of possible system states is huge, and in the test cases it is necessary to include states that trigger all the relevant global system behaviour, e.g., an important self-adaptation capability [82]. The decision about which global system states should be actually brought out by test cases is a difficult trade-off between keeping the number of such states reasonably small, and covering all the relevant situations [117]. In order to find a good trade-off in a (semi-)automatic way, the availability of a formal system model and/or of formal requirements is a promising direction to be pursued.

Test Cases: Outcomes. The nature of CCPEs poses challenges also for the determination of the test outcome, in terms of the equality between an *expected* result (test oracle), and the *actual* result of applying certain inputs to a certain system state. The (automatic) computation of the expected result requires the availability of a formal specification, similarly as the determination of relevant test inputs discussed above [117]. However, also the determination of the actual result is not trivial, for at least two reasons. First, the global outcome of the test must be determined as the value of a formula that must be computed by potentially taking into account the local states of a large number of system entities; in order to compute it in a distributed way, techniques such as distributed Runtime Verification (RV) may be adopted [13]. Second, the resulting global state may take some time to materialize due to delays introduced by the communications between the CCPE entities. Even when a CCPE behaviour is self-stabilising [133], then, it is key to allow enough time for the stabilisation before finalising the test result.

Monitoring and runtime verification. As the runtime execution of a CCPEs is subject to external and often unpredictable influences, a priori SE methods are usually not sufficient to guarantee the desired outcomes. Therefore, they have to be complemented by runtime monitoring approaches, both as separate tools flagging when manual intervention is needed, and as integrated parts of the system triggering automatic reactions. However, several challenges arise when performing runtime monitoring on CCPE. A first challenge is designing appropriate specification logics, that need to balance two opposite forces: expressiveness and simplicity. On expressiveness, a logic should capture enough relevant properties of systems situated in space and evolving over time. On simplicity, it should allow an intuitive understanding to enhance its usability, also among domain experts not proficient in modal logics. This tension has led to many different logics being developed so far [12, 13, 84, 94], and leaves room for improvement in future works.

A further challenge is computing monitor results from CCPE data. Some approaches such as have been restricted so far to *offline monitoring*, performed remotely on a complete trace of events gathered from the whole historical data of a CCPE, limiting their applicability in real-time [94]. Other approaches allow for *centralised online monitoring* [84], still requiring to gather all events on a single remote computer, but allowing to compute monitor results in real-time from such event traces. Limited research has been carried out so far on *decentralised monitoring* [12, 13], in which monitors are integrated within the monitored application and run on the same distributed devices. Each device computes its own view of the monitored properties according to the knowledge available to it, without need for a central coordinator. Although this approach

allows for greater resilience and faster reaction times of monitors, it poses additional challenges that have so far limited the monitored logic expressiveness. Future works could improve the current expressiveness limits in this context.

4.4 Integration with Humans

An important characteristic of CCPEs is that they typically involve both physical components (such as sensors, robots, drones, ...) as well as humans. The interaction between humans and the other cyber-physical entities can be either direct (e.g., through voice and gestures directly captured with microphones and cameras), or indirect, with the human interacting through wearable devices. Two scenarios (of increasing complexity) of integration between humans and CCPEs can be envisioned and pose peculiar challenges.

Humans controlling CCPEs. Humans and physical devices interact with strict, rigid asymmetric roles. We can consider humans as external, although strictly connected with the CCPE. In this scenario, the humans typically request services from the CCPEs, and/or perform some control over them [132]. In a variation of the scenario, instead of commands, the humans may provide relevant inputs by carrying wearables or smartphones, e.g. in healthcare [29].

One crucial aspect in this kind of systems is the cognitive load affecting the human(s) in charge of controlling the CCPE, especially when the latter contains many elements, as in a swarm [102]. Another important aspect is the communication modality between humans and devices (e.g., robots), which can involve speech, gesture, haptics (if humans and devices are physically close), or screen-based UIs and Virtual Reality (if the humans and devices are remote) [45].

The main challenges for this kind of scenario are thus mainly related with Human-Machine Interface (HMI), and in particular multi-modal interfaces that improve the human user effectiveness and comfort. A fundamental issue that is related with HMI is the level of autonomy of the CCPE w.r.t. the human: the *right* level of autonomy should be ideally adjusted dynamically to maximize the performance of the human high-level control over the CCPE [91].

Humans as CCPE Entities. Humans and physical devices act as a single CCPE. In this kind of scenario, there isn't a rigid hierarchy where humans give (high-level) commands and CCPE entities collectively execute them; instead, the roles of humans and robots are equal, or at least overlapping, and (partially) interchangeable. Interesting applications of these hybrid CCPEs include industrial processes [63, 73, 150], as well as rescue missions [64]. In order to fully take part into the CCPE, humans typically have to carry some devices (smartphones, wearables, ...) used to provide inputs and outputs from/to the human. The main challenge posed by this kind of systems is that they should run collective algorithms that take into account and exploit the differences between humans and artificial entities (e.g., intelligence, or speed), while at the same time considering them as (partially) interchangeable elements of the system. This means that the system must have a more or less sophisticated model of its entities, and adapt its decisions to the involved entities.

4.5 Learning collective behaviour

Despite years of research into synthesizing collective behaviours, finding an effective and scalable method to address the challenges associated with learning in such systems remains a complex issue [67]. The intricacy of multi-agent systems escalates significantly as the number of agents increases [50, 66]; this amplifies the complexity of the system's dynamics, complicating the process of discerning the influence of individual actions on the collective outcome. Below, we delineate some paramount challenges associated with learning in collective behaviour.

Multi-agent Credit Assignment. A paramount issue within multi-agent systems is the *multi-agent credit assignment* challenge, as highlighted by Nguyen et al. [96]. This problem revolves around the precise identification and rewarding of individual agent actions that contribute positively towards the collective goal. Techniques such as COMA and difference rewards [128] have been developed to tackle this challenge. However, these approaches often entail a significant computational burden, rendering them less viable for deployment in large-scale systems. The core strategy of these methods involves calculating rewards for agents by assessing the impact of their actions on the collective outcome—a process that requires simulating the system's state with and without the agent's action to find the differential effect [5]. This dual-simulation approach, while conceptually appealing for its accuracy in attributing credit, is notably resource-intensive and may not scale efficiently with the complexity or size of the system [55].

Online Learning. In such systems, agents should learn in real-time, adapting to changes in the environment and the behaviour of other agents without leveraging a central trainer. However, unlike single-agent systems, where the environment typically exhibits stationary characteristics, online learning in multi-agent systems introduces a non-stationary environment [28, 50, 66]. This complexity makes it difficult to determine whether changes are due to environmental responses or agent behaviour change, potentially leading to undesirable emergent behaviours and loss of control over collective learning [101, 146]. Thus, moving from the current state of the art, which mainly focuses on offline learning with a centralised training/decentralised execution approach [61, 78], to decentralised online learning is a crucial challenge to be further investigated [50].

Transfer learning. Another aspect of learning involves the *transfer* of knowledge from one domain to another. The capability to apply knowledge acquired in one context to another, but similar, context presents a considerable challenge [44]. Even if several solutions have been proposed so far to address this issue [21], the complexity of transfer learning in CCPEs underscores the need for novel approaches to facilitate knowledge transfer across contexts effectively. Indeed, in multiagent systems there are several axes to be handled, such as the communication between agents, the different roles of agents, the different capabilities of agents, and the different environments in which agents operate [44]. In single agent learning, a novel trend consist in leveraging large pre-trained models (i.e., *foundational models*) to facilitate learning in new tasks [111]. The adoption of foundational models in CCPEs could mark a shift toward more efficient and effective learning mechanisms, suggesting a promising avenue for future exploration.

5 CONCLUSION

In this paper, we presented challenges, current research efforts, and future research directions for a collective computing paradigm in software engineering. We showed the relevance of this paradigm given the growing interest in large-scale cyber-physical ecosystems. By reviewing key themes and relevant contributions in CCPEs engineering, we categorised current research efforts on both techniques, abstractions, and tools. From this, we identified the challenges ahead that will require innovative solutions. These include the handling of homogeneity and heterogeneity; the development of DSLs, middleware and tools; the bridging of global and local perspectives in system analysis, design, and implementation; the integration with humans; and collective learning approaches. Addressing these challenges will be essential for unlocking the full potential of CCPEs and advancing the state of the art in software engineering cyber-physical ecosystems research.

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REFERENCES

- [1] Dhaminda B. Abeywickrama, Nicola Bicocchi, Marco Mamei, and Franco Zambonelli. 2020. The SOTA approach to engineering collective adaptive systems. *Int. J. Softw. Tools Technol. Transf.* 22, 4 (2020), 399–415. <https://doi.org/10.1007/S10009-020-00554-3>
- [2] Gregory D. Abowd. 2016. Beyond Weiser: From Ubiquitous to Collective Computing. *Computer* 49, 1 (2016), 17–23. <https://doi.org/10.1109/MC.2016.22>
- [3] Afsoon Afzal, Claire Le Goues, Michael Hilton, and Christopher Steven Timperley. 2020. A Study on Challenges of Testing Robotic Systems. In *2020 IEEE 13th International Conference on Software Testing, Validation and Verification (ICST)*. 96–107. <https://doi.org/10.1109/ICST46399.2020.00020>
- [4] Afsoon Afzal, Deborah S. Katz, Claire Le Goues, and Christopher S. Timperley. 2021. Simulation for Robotics Test Automation: Developer Perspectives. In *2021 14th IEEE Conference on Software Testing, Verification and Validation (ICST)*. 263–274. <https://doi.org/10.1109/ICST49551.2021.00036>
- [5] Adrian K. Agogino and Kagan Turner. 2004. Unifying Temporal and Structural Credit Assignment Problems. In *3rd International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2004)*, 19–23 August 2004, New York, NY, USA. IEEE Computer Society, 980–987. <https://doi.org/10.1109/AAMAS.2004.10098>
- [6] Gianluca Aguzzi, Roberto Casadei, and Mirko Viroli. 2022. Machine Learning for Aggregate Computing: a Research Roadmap. In *42nd IEEE International Conference on Distributed Computing Systems, ICDCS Workshops, Bologna, Italy, July 10, 2022*. IEEE, 119–124. <https://doi.org/10.1109/ICDCSW56584.2022.00032>
- [7] Gianluca Aguzzi, Roberto Casadei, and Mirko Viroli. 2022. Towards Reinforcement Learning-based Aggregate Computing. In *Coordination Models and Languages - 24th IFIP WG 6.1 International Conference, COORDINATION 2022, Proceedings (Lecture Notes in Computer Science, Vol. 13271)*. Springer, 72–91. https://doi.org/10.1007/978-3-031-08143-9_5
- [8] Rima Al Ali, Lubomir Bulej, Jan Kofron, and Tomás Bures. 2022. A guide to design uncertainty-aware self-adaptive components in Cyber-Physical Systems. *Future Gener. Comput. Syst.* 128 (2022), 466–489. <https://doi.org/10.1016/J.FUTURE.2021.10.027>
- [9] Yehia Abd Alrahman, Rocco De Nicola, and Michele Loreti. 2020. Programming interactions in collective adaptive systems by relying on attribute-based communication. *Sci. Comput. Program.* 192 (2020), 102428. <https://doi.org/10.1016/J.SCICO.2020.102428>
- [10] Majed Alwateer, Seng W. Loke, and Niroshinie Fernando. 2019. Enabling Drone Services: Drone Crowdsourcing and Drone Scripting. *IEEE Access* 7 (2019), 110035–110049. <https://doi.org/10.1109/ACCESS.2019.2933234>
- [11] Paolo Arcaini, Xiao-Yi Zhang, and Fuyuki Ishikawa. 2021. Targeting Patterns of Driving Characteristics in Testing Autonomous Driving Systems. In *2021 14th IEEE Conference on Software Testing, Verification and Validation (ICST)*. 295–305. <https://doi.org/10.1109/ICST49551.2021.00042>
- [12] Giorgio Audrito, Roberto Casadei, Ferruccio Damiani, Volker Stoltz, and Mirko Viroli. 2021. Adaptive distributed monitors of spatial properties for cyber-physical systems. *J. Syst. Softw.* 175 (2021), 110908. <https://doi.org/10.1016/J.JSS.2021.110908>
- [13] Giorgio Audrito, Ferruccio Damiani, Volker Stoltz, Gianluca Torta, and Mirko Viroli. 2022. Distributed runtime verification by past-CTL and the field calculus. *J. Syst. Softw.* 187 (2022), 111251. <https://doi.org/10.1016/j.jss.2022.111251>
- [14] Giorgio Audrito, Mirko Viroli, Ferruccio Damiani, Danilo Pianini, and Jacob Beal. 2019. A Higher-Order Calculus of Computational Fields. *ACM Trans. Comput. Logic* 20, 1, Article 5 (jan 2019), 55 pages. <https://doi.org/10.1145/3285956>
- [15] Jacob Beal, Stefan Dulman, Kyl Usbeck, Mirko Viroli, and Nikolaus Correll. 2013. Organizing the Aggregate: Languages for Spatial Computing. In *Formal and Practical Aspects of Domain-Specific Languages: Recent Developments*. IGI Global, Chapter 16, 436–501. <https://doi.org/10.4018/978-1-4666-2092-6.ch016>
- [16] Christian Becker, Christine Julien, Philippe Lalanda, and Franco Zambonelli. 2019. Pervasive computing middleware: current trends and emerging challenges. *CCF Trans. Pervasive Comput. Interact.* 1, 1 (2019), 10–23. <https://doi.org/10.1007/S42486-019-00005-2>
- [17] Kirstie L. Bellman, Jean Botet, Ada Diaconescu, Lukas Esterle, Christian Gruhl, Christopher Landauer, Peter R. Lewis, Phyllis R. Nelson, Evangelos Pournaras, Anthony Stein, and Sven Tomforde. 2021. Self-improving system integration: Mastering continuous change. *Future Gener. Comput. Syst.* 117 (2021), 29–46. <https://doi.org/10.1016/J.FUTURE.2020.11.019>
- [18] Marco Bernardo, Rocco De Nicola, and Jane Hillston (Eds.). 2016. *Formal Methods for the Quantitative Evaluation of Collective Adaptive Systems - 16th International School on Formal Methods for the Design of Computer, Communication, and Software Systems, SFM 2016, Bertinoro, Italy, June 20-24, 2016, Advanced Lectures*. Lecture Notes in Computer Science, Vol. 9700. Springer. <https://doi.org/10.1007/978-3-319-34096-8>
- [19] Olivier Boissier, Rafael H Bordini, Jomi Hubner, and Alessandro Ricci. 2020. *Multi-agent oriented programming: programming multi-agent systems using JaCaMo*. MIT Press.
- [20] Eric Bonabeau, Marco Dorigo, and Guy Theraulaz. 1999. *Swarm intelligence: from natural to artificial systems*. Oxford university press.
- [21] Georgios Boutsikouls, Ioannis Partalas, and Ioannis P. Vlahavas. 2011. Transfer Learning in Multi-Agent Reinforcement Learning Domains. In *Recent Advances in Reinforcement Learning - 9th European Workshop, EWRL 2011, Athens, Greece, September 9-11, 2011, Revised Selected Papers (Lecture Notes in Computer Science, Vol. 7188)*, Scott Sanner and Marcus Hutter (Eds.). Springer, 249–260. https://doi.org/10.1007/978-3-642-29946-9_25
- [22] Michele Braccini, Andrea Roli, Marco Villani, and Roberto Serra. 2016. Automatic Design of Boolean Networks for Cell Differentiation. In *Advances in Artificial Life, Evolutionary Computation, and Systems Chemistry - 11th Italian Workshop, WIVACE 2016, Fisciano, Italy, October 4-6, 2016, Revised Selected Papers (Communications in Computer and Information Science, Vol. 708)*. Springer, 91–102. https://doi.org/10.1007/978-3-319-57711-1_8
- [23] Manuele Brambilla, Eliseo Ferrante, Mauro Birattari, and Marco Dorigo. 2013. Swarm robotics: a review from the swarm engineering perspective. *Swarm Intell.* 7, 1 (2013), 1–41. <https://doi.org/10.1007/S11721-012-0075-2>
- [24] Manfred Broy and Albrecht Schmidt. 2014. Challenges in Engineering Cyber-Physical Systems. *Computer* 47, 2 (2014), 70–72. <https://doi.org/10.1109/MC.2014.30>
- [25] Antonio Bucciarone and Marina Mongiello. 2019. Ten Years of Self-adaptive Systems: From Dynamic Ensembles to Collective Adaptive Systems. In *From Software Engineering to Formal Methods and Tools, and Back (Lecture Notes in Computer Science, Vol. 11865)*. Springer, 19–39. https://doi.org/10.1007/978-3-030-30985-5_3
- [26] Bruno Buchberger. 2023. Automated programming, symbolic computation, machine learning: my personal view. *Ann. Math. Artif. Intell.* 91, 5 (2023), 569–589. <https://doi.org/10.1007/S10472-023-09894-7>
- [27] Tomás Bures, Ilias Gerostathopoulos, Petr Hnětnýka, Jaroslav Kežník, Michal Kit, and František Plášil. 2013. DEECO: an ensemble-based component system. In *CBSE'13, Proceedings of the 16th ACM SIGSOFT Symposium on Component Based Software Engineering*. ACM, 81–90. <https://doi.org/10.1145/2465449.2465462>
- [28] Lucian Busoni, Robert Babuska, and Bart De Schutter. 2008. A Comprehensive Survey of Multiagent Reinforcement Learning. *IEEE Trans. Syst. Man Cybern. Part C* 38, 2 (2008), 156–172.
- [29] Davide Calvaresi, Mauro Marinoni, Aldo Franco Dragoni, Roger Hilfiker, and Michael Schumacher. 2019. Real-time multi-agent systems for telerehabilitation scenarios. *Artificial Intelligence in Medicine* 96 (2019), 217–231. <https://doi.org/10.1016/J.ARTMED.2019.02.001>
- [30] Roberto Casadei. 2023. Artificial Collective Intelligence Engineering: A Survey of Concepts and Perspectives. *Artif. Life* 29, 4 (2023), 433–467. https://doi.org/10.1162/ARTL_A_00408
- [31] Roberto Casadei. 2023. Macroprogramming: Concepts, State of the Art, and Opportunities of Macroscopic Behaviour Modelling. *ACM Comput. Surv.* 55, 13s (2023), 275:1–275:37. <https://doi.org/10.1145/3579353>
- [32] Roberto Casadei, Giancarlo Fortino, Danilo Pianini, Andrea Placuzzi, Claudio Savaglio, and Mirko Viroli. 2022. A Methodology and Simulation-Based Toolchain for Estimating Deployment Performance of Smart Collective Services at the Edge. *IEEE Internet Things J.* 9, 20 (2022), 20136–20148. <https://doi.org/10.1109/JIOT.2022.3172470>

- [33] Roberto Casadei, Danilo Pianini, Andrea Placuzzi, Mirko Viroli, and Danny Weyns. 2020. Pulverization in Cyber-Physical Systems: Engineering the Self-Organizing Logic Separated from Deployment. *Future Internet* 12, 11 (2020), 203. <https://doi.org/10.3390/FI12110203>
- [34] Roberto Casadei and Mirko Viroli. 2018. Collective Abstractions and Platforms for Large-Scale Self-Adaptive IoT. In *2018 IEEE 3rd International Workshops on Foundations and Applications of Self* Systems (FAS*W), Trento, Italy, September 3-7, 2018*. IEEE, 106–111. <https://doi.org/10.1109/FAS-W.2018.00033>
- [35] Christos G. Cassandras and Stephane Lafontaine. 2021. *Introduction to Discrete Event Systems* (3rd ed.). Springer Publishing Company, Incorporated.
- [36] Valentina Castiglioni, Michele Loreti, and Simona Tini. 2023. A framework to measure the robustness of programs in the unpredictable environment. *Log. Methods Comput. Sci.* 19, 3 (2023). [https://doi.org/10.46298/LMCS-19\(3:2\)2023](https://doi.org/10.46298/LMCS-19(3:2)2023)
- [37] Swarat Chaudhuri, Kevin Ellis, Oleksandr Polozov, Rishabh Singh, Armando Solar-Lezama, and Yisong Yue. 2021. Neurosymbolic Programming. *Found. Trends Program. Lang.* 7, 3 (2021), 158–243. <https://doi.org/10.1561/2500000049>
- [38] Bo Cheng, Da Zhu, Shuai Zhao, and Junliang Chen. 2016. Situation-Aware IoT Service Coordination Using the Event-Driven SOA Paradigm. *IEEE Trans. Netw. Serv. Manag.* 13, 2 (2016), 349–361. <https://doi.org/10.1109/TNSM.2016.2541171>
- [39] François Collet. 2019. On the measure of intelligence. *arXiv preprint arXiv:1911.01547* (2019).
- [40] Andrew G. Clark, Neil Walkinshaw, and Robert M. Hierons. 2021. Test case generation for agent-based models: A systematic literature review. *Information and Software Technology* 135 (2021). <https://doi.org/10.1016/j.infsof.2021.106567>
- [41] Marco Conti, Sajal K. Das, Chatschik Bisdikian, Mohan Kumar, Lionel M. Ni, Andrea Passarella, George Roussos, Gerhard Tröster, Gene Tsudik, and Franco Zambonelli. 2012. Looking ahead in pervasive computing: Challenges and opportunities in the era of cyber-physical convergence. *Pervasive Mob. Comput.* 8, 1 (2012), 2–21. <https://doi.org/10.1016/j.pmcj.2011.10.001>
- [42] Hélène Couillon, Ludovic Henrio, Frédéric Loulergue, and Simon Robillard. 2023. Component-Based Distributed Software Reconfiguration: A Verification-Oriented Survey. *ACM Comput. Surv.* (may 2023). <https://doi.org/10.1145/3595376>
- [43] Luís Cruz-Filipe and Fabrizio Montesi. 2020. A core model for choreographic programming. *Theor. Comput. Sci.* 802 (2020), 38–66. <https://doi.org/10.1016/j.tcs.2019.07.005>
- [44] Felipe Leno da Silva and Anna Helena Reali Costa. 2019. A Survey on Transfer Learning for Multiagent Reinforcement Learning Systems. *J. Artif. Intell. Res.* 64 (2019), 645–703. <https://doi.org/10.1613/JAIR.1.11396>
- [45] Abhinav Dahiya, Alexander M. Aroyo, Kerstin Dautenhahn, and Stephen L. Smith. 2023. A survey of multi-agent Human-Robot Interaction systems. *Robotics and Autonomous Systems* 161 (2023), 104335. <https://doi.org/10.1016/j.robot.2022.104335>
- [46] Marcos Dias de Assunção, Alexandre Da Silva Veith, and Rajkumar Buyya. 2018. Distributed data stream processing and edge computing: A survey on resource elasticity and future directions. *J. Netw. Comput. Appl.* 103 (2018), 1–17. <https://doi.org/10.1016/j.jnca.2017.12.001>
- [47] Audelia Gumarus Dharmawan, Gim Song Soh, Shaohui Foong, Roland Bouffanais, and Kristin L. Wood. 2019. Design innovation of mesoscale robotic swarms: applications to cooperative urban sensing and mapping. *Frontiers Inf. Technol. Electron. Eng.* 20, 12 (2019), 1618–1631. <https://doi.org/10.1631/FITEE.1900384>
- [48] Marco Dorigo, Guy Theraulaz, and Vito Trianni. 2020. Reflections on the future of swarm robotics. *Science Robotics* 5, 49 (Dec. 2020), eabe4385. <https://doi.org/10.1126/scirobotics.abe4385>
- [49] Nicola Dragoni, Saverio Giallorenzo, Alberto Lluch-Lafuente, Manuel Mazzara, Fabrizio Montesi, Ruslan Mustafin, and Larisa Safina. 2017. Microservices: Yesterday, Today, and Tomorrow. In *Present and Ulterior Software Engineering*. Springer, 195–216. https://doi.org/10.1007/978-3-319-67425-4_12
- [50] Wei Du and Shifei Ding. 2021. A survey on multi-agent deep reinforcement learning: from the perspective of challenges and applications. *Artif. Intell. Rev.* 54, 5 (2021), 3215–3238. <https://doi.org/10.1007/S10462-020-09938-Y>
- [51] Jose Luis Fernandez-Marquez, Giovanna Di Marzo Serugendo, Sara Montagna, Mirko Viroli, and Josep Lluís Arcos. 2013. Description and composition of bio-inspired design patterns: a complete overview. *Nat. Comput.* 12, 1 (2013), 43–67. <https://doi.org/10.1007/S10147-012-9324-Y>
- [52] Ana Juan Ferrer, Sören Becker, Florian Schmidt, Lauritz Thamsen, and Odej Kao. 2021. Towards a Cognitive Compute Continuum: An Architecture for Ad-Hoc Self-Managed Swarms. In *21st IEEE/ACM International Symposium on Cluster, Cloud and Internet Computing, CCGrid 2021*. IEEE, 634–641. <https://doi.org/10.1109/CCGRID51090.2021.00076>
- [53] Alois Ferscha, Paul Lukowicz, and Franco Zambonelli. 2014. The superorganism of massive collective wearables. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing, UbiComp '14 Adjunct Publication*. ACM, 1077–1084. <https://doi.org/10.1145/2638728.2659396>
- [54] Dario Floreano and Laurent Keller. 2010. Evolution of Adaptive Behaviour in Robots by Means of Darwinian Selection. *PLoS Biology* 8, 1 (Jan. 2010), e1000292. <https://doi.org/10.1371/journal.pbio.1000292>
- [55] Jakob N. Foerster, Gregory Farquhar, Triantafyllos Afouras, Nantas Nardelli, and Shimon Whiteson. 2018. Counterfactual Multi-Agent Policy Gradients. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18), the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18)*. AAAI Press, 2974–2982. <https://doi.org/10.1609/AAAI.V32I1.11794>
- [56] Gianpiero Francesca, Manuele Brambilla, Arne Brutschy, Lorenzo Garattini, Roman Miletitch, Gaëtan Podevijn, Andreagiovanni Reina, Touraj Soleymani, Mattia Salvato, Carlo Pincioli, Franco Mascia, Vito Trianni, and Mauro Birattari. 2015. AutoMoDe-Chocolate: automatic design of control software for robot swarms. *Swarm Intell.* 9, 2–3 (2015), 125–152. <https://doi.org/10.1007/S11721-015-0107-9>
- [57] Gianpiero Francesca, Manuele Brambilla, Arne Brutschy, Vito Trianni, and Mauro Birattari. 2014. AutoMoDe: A novel approach to the automatic design of control software for robot swarms. *Swarm Intell.* 8, 2 (2014), 89–112. <https://doi.org/10.1007/S11721-014-0092-4>
- [58] Carlos Gershenson, Vito Trianni, Justin Werfel, and Hiroki Sayama. 2020. Self-Organization and Artificial Life. *Artif. Life* 26, 3 (2020), 391–408. https://doi.org/10.1162/art_a_00324
- [59] Jacques Gignoux, Guillaume Chérel, Ian D. Davies, Shayne R. Flint, and Eric Lateltin. 2017. Emergence and complex systems: The contribution of dynamic graph theory. *Ecological Complexity* 31 (Sept. 2017), 34–49. <https://doi.org/10.1016/j.ecocom.2017.02.006>
- [60] Nicola Del Giudice, Lorenzo Matteucci, Michela Quadrini, Aniqa Rehman, and Michele Loreti. 2022. Sibila: A Tool for Reasoning about Collective Systems. In *Coordination Models and Languages - 24th IFIP WG 6.1 International Conference, COORDINATION 2022, Proceedings (LNCS, Vol. 13271)*. Springer, 92–98. https://doi.org/10.1007/978-3-031-08143-9_6
- [61] Sven Gronauer and Klaus Diepold. 2022. Multi-agent deep reinforcement learning: a survey. *Artif. Intell. Rev.* 55, 2 (2022), 895–943. <https://doi.org/10.1007/S10462-021-09996-W>
- [62] Sumit Gulwani, Oleksandr Polozov, and Rishabh Singh. 2017. Program Synthesis. *Found. Trends Program. Lang.* 4, 1–2 (2017), 1–119. <https://doi.org/10.1561/2500000010>
- [63] Daqiang Guo. 2024. Fast scheduling of human-robot teams collaboration on synchronised production-logistics tasks in aircraft assembly. *Robotics and Computer-Integrated Manufacturing* 85 (2024). <https://doi.org/10.1016/j.rcim.2023.102620>
- [64] Lydia Habib, Marie-Pierre Pacaux-Lemoine, and Patrick Millot. 2018. Human-Robots Team Cooperation in Crisis Management Mission. In *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. 3219–3224. <https://doi.org/10.1109/SMC.2018.00545>
- [65] Feijuan He, Yudai Pan, Qika Lin, Xianglin Miao, and Zhouguo Chen. 2019. Collective Intelligence: A Taxonomy and Survey. *IEEE Access* 7 (2019), 170213–170225. <https://doi.org/10.1109/ACCESS.2019.2955677>
- [66] Pablo Hernandez-Leal, Bilal Kartal, and Matthew E. Taylor. 2018. Is multiagent deep reinforcement learning the answer or the question? A brief survey. *CoRR* abs/1810.05587 (2018). arXiv:1810.05587 <http://arxiv.org/abs/1810.05587>
- [67] Pablo Hernandez-Leal, Bilal Kartal, and Matthew E. Taylor. 2019. A survey and critique of multiagent deep reinforcement learning. *Auton. Agents Multi Agent Syst.* 33, 6 (2019), 750–797. <https://doi.org/10.1007/S10458-019-09421-1>
- [68] Dan Hirsch, Paola Inverardi, and Ugo Montanari. 1998. Graph grammars and constraint solving for software architecture styles. In *Proceedings of the Third International Workshop on Software Architecture, ISAW '98*. ACM, 69–72. <https://doi.org/10.1145/288408.288426>
- [69] Mohammad Aminul Hoque, Md. Mahmud Hossain, Shahid Al Noor, S. M. Riazul Islam, and Ragib Hasan. 2022. IoTaaS: Drone-Based Internet of Things as a Service Framework for Smart Cities. *IEEE Internet Things J.* 9, 14 (2022), 12425–12439. <https://doi.org/10.1109/IJOT.2021.3137362>
- [70] Jennifer Horkoff, Fatma Basak Aydemir, Evellen Cardoso, Tong Li, Alejandro Maté, Elda Paja, Mattia Salnitri, Luca Piras, John Mylopoulos, and Paolo Giorgini. 2019. Goal-oriented requirements engineering: an extended systematic mapping study. *Requir. Eng.* 24, 2 (2019), 133–160. <https://doi.org/10.1007/S00766-017-0280-Z>
- [71] Bryan Horling and Victor R. Lesser. 2004. A survey of multi-agent organizational paradigms. *Knowl. Eng. Rev.* 19, 4 (2004), 281–316. <https://doi.org/10.1017/S0269888905000317>
- [72] Omar Inverso, Catia Trubiani, and Emilio Tuosto. 2020. Abstractions for Collective Adaptive Systems. In *Leveraging Applications of Formal Methods, Verification and Validation: Engineering Principles - 9th International Symposium on Leveraging Applications of Formal Methods, IsoLa 2020, Proceedings, Part II (LNCS, Vol. 12477)*. Springer, 243–260. https://doi.org/10.1007/978-3-030-61470-6_15
- [73] Jana Jost, Thomas Kirks, and Benedikt Mättig. 2017. Multi-agent systems for decentralized control and adaptive interaction between humans and machines for industrial environments. In *2017 7th IEEE International Conference on System Engineering and Technology (ICSET)*. 95–100. <https://doi.org/10.1109/ICSEngT.2017.8123427>
- [74] Iwens Gervásio Sene Júnior, Thalia S. Santana, Renato F. Bulcão-Neto, and Barry Porter. 2022. The state of the art of macroprogramming in IoT: An update. *J.*

- Internet Serv. Appl.* 13, 1 (2022), 54–65. <https://doi.org/10.5753/JISA.2022.2372>
- [75] Nanxi Kang, Zheming Liu, Jennifer Rexford, and David Walker. 2013. Optimizing the “one big switch” abstraction in software-defined networks. In *Conference on emerging Networking Experiments and Technologies (CoNEXT’13), Proceedings of ACM*, 13–24. <https://doi.org/10.1145/2535372.2535373>
- [76] Daniela Kengyel, Heiko Hamann, Payam Zahadat, Gerald Radspieler, Franz Wotawa, and Thomas Schmickl. 2015. Potential of Heterogeneity in Collective Behaviors: A Case Study on Heterogeneous Swarms. In *PRIMA 2015: Principles and Practice of Multi-Agent Systems - 18th International Conference, Proceedings (LNCS, Vol. 9387)*. Springer, 201–217. https://doi.org/10.1007/978-3-319-25524-8_13
- [77] Jeffrey O. Kephart and David M. Chess. 2003. The Vision of Autonomic Computing. *Computer* 36, 1 (2003), 41–50. <https://doi.org/10.1109/MC.2003.1160055>
- [78] Landon Kraemer and Bikramjit Banerjee. 2016. Multi-agent reinforcement learning as a rehearsal for decentralized planning. *Neurocomputing* 190 (2016), 82–94. <https://doi.org/10.1016/J.NEUCOM.2016.01.031>
- [79] Angel Lagares Lemos, Florian Daniel, and Boualem Benatallah. 2016. Web Service Composition: A Survey of Techniques and Tools. *ACM Comput. Surv.* 48, 3 (2016), 33:1–33:41. <https://doi.org/10.1145/2831270>
- [80] Meng Li, Pan Pei, F. Richard Yu, Pengbo Si, Yu Li, Enchang Sun, and Yanhua Zhang. 2022. Cloud-Edge Collaborative Resource Allocation for Blockchain-Enabled Internet of Things: A Collective Reinforcement Learning Approach. *IEEE Internet Things J.* 9, 22 (2022), 23115–23129. <https://doi.org/10.1109/JIOT.2022.3185289>
- [81] Shancang Li, Li Da Xu, and Shanshan Zhao. 2015. The internet of things: a survey. *Inf. Syst. Frontiers* 17, 2 (2015), 243–259. <https://doi.org/10.1007/S10796-014-9492-7>
- [82] Yoo Jin Lim, Eunkyoung Jee, Donghwan Shin, and Doo-Hwan Bae. 2015. Efficient Testing of Self-Adaptive Behaviors in Collective Adaptive Systems. In *39th IEEE Annual Computer Software and Applications Conference, COMPSAC 2015, Volume 2*. IEEE Computer Society, 216–221. <https://doi.org/10.1109/COMPSAC.2015.131>
- [83] Michele Loreti and Jane Hillston. 2016. Modelling and Analysis of Collective Adaptive Systems with CARMA and its Tools. In *Formal Methods for the Quantitative Evaluation of Collective Adaptive Systems - 16th International School on Formal Methods for the Design of Computer, Communication, and Software Systems, SFM 2016, Advanced Lectures (LNCS, Vol. 9700)*. Springer, 83–119. https://doi.org/10.1007/978-3-319-34096-8_4
- [84] Meiyi Ma, Ezio Bartocci, Eli Lifland, John A. Stankovic, and Lu Feng. 2021. A Novel Spatial-Temporal Specification-Based Monitoring System for Smart Cities. *IEEE Internet Things J.* 8, 15 (2021), 11793–11806. <https://doi.org/10.1109/JIOT.2021.3069943>
- [85] Ivano Malavolta, Patricia Lago, Henry Muccini, Patrizio Pelliccione, and Antony Tang. 2013. What Industry Needs from Architectural Languages: A Survey. *IEEE Trans. Software Eng.* 39, 6 (2013), 869–891. <https://doi.org/10.1109/TSE.2012.74>
- [86] Thomas W Malone and Michael S Bernstein. 2022. *Handbook of collective intelligence*. MIT press.
- [87] Marco Mamei and Franco Zambonelli. 2009. Programming pervasive and mobile computing applications: The TOTA approach. *ACM Trans. Softw. Eng. Methodol.* 18, 4 (2009), 15:1–15:56. <https://doi.org/10.1145/1538942.1538945>
- [88] Claudio Masolo, Laure Vieu, Roberta Ferrario, Stefano Borgo, and Daniele Porello. 2020. Pluralities, Collectives, and Composites. In *Formal Ontology in Information Systems - Proceedings of the 11th International Conference, FOIS 2020 (Frontiers in Artificial Intelligence and Applications, Vol. 330)*. IOS Press, 186–200. <https://doi.org/10.3233/FAIA200671>
- [89] George E. Mobus and Michael C. Kalton. 2015. *Principles of Systems Science*. Springer.
- [90] Fabrizio Montesi. 2023. *Introduction to Choreographies*. Cambridge University Press.
- [91] Salama A Mostafa, Mohd Sharifuddin Ahmad, and Aida Mustapha. 2019. Adjustable autonomy: a systematic literature review. *Artificial Intelligence Review* 51 (2019), 149–186.
- [92] Luca Mottola and Gian Pietro Picco. 2011. Programming wireless sensor networks: Fundamental concepts and state of the art. *ACM Comput. Surv.* 43, 3 (2011), 19:1–19:51. <https://doi.org/10.1145/1922649.1922656>
- [93] Maurizio Murgia, Riccardo Pincioli, Catia Trubiani, and Emilio Tuosto. 2023. Comparing performance abstractions for collective adaptive systems. *Int. J. Softw. Tools Technol. Transf.* 25, 5 (2023), 785–798. <https://doi.org/10.1007/S10009-023-00728-9>
- [94] Laura Nenzi, Ezio Bartocci, Luca Bortolussi, and Michele Loreti. 2022. A Logic for Monitoring Dynamic Networks of Spatially-distributed Cyber-Physical Systems. *Log. Methods Comput. Sci.* 18, 1 (2022). [https://doi.org/10.46298/LMCS-18\(1-4\)2022](https://doi.org/10.46298/LMCS-18(1-4)2022)
- [95] Ryan Newton, Arvind, and Matt Welsh. 2005. Building up to macroprogramming: an intermediate language for sensor networks. In *Proceedings of the 4th International Symposium on Information Processing in Sensor Networks, IPSN 2005*. IEEE, 37–44. <https://doi.org/10.1109/IPSN.2005.1440891>
- [96] Duc Thien Nguyen, Akshat Kumar, and Hoong Chuin Lau. 2018. Credit Assignment For Collective Multiagent RL With Global Rewards. In *Advances in Neural Information Processing Systems 31: Annual Conference on Neural Information Processing Systems 2018, NeurIPS 2018*, 8113–8124.
- [97] Rocco De Nicola, Stefan Jähnichen, and Martin Wirsing. 2020. Rigorous engineering of collective adaptive systems: special section. *Int. J. Softw. Tools Technol. Transf.* 22, 4 (2020), 389–397. <https://doi.org/10.1007/s10009-020-00565-0>
- [98] Rocco De Nicola, Michele Loreti, Rosario Pugliese, and Francesco Tiezzi. 2014. A Formal Approach to Autonomic Systems Programming: The SCEL Language. *ACM Trans. Auton. Adapt. Syst.* 9, 2 (2014), 7:1–7:29. <https://doi.org/10.1145/2619998>
- [99] Victor Noël and Franco Zambonelli. 2015. Methodological Guidelines for Engineering Self-organization and Emergence. In *Software Engineering for Collective Autonomic Systems - The ASCENS Approach*. Lecture Notes in Computer Science, Vol. 8998. Springer, 355–378. https://doi.org/10.1007/978-3-319-16310-9_10
- [100] Anne-Cécile Orgerie, Marcos Dias de Assunção, and Laurent Lefèvre. 2013. A survey on techniques for improving the energy efficiency of large-scale distributed systems. *ACM Comput. Surv.* 46, 4 (2013), 47:1–47:31. <https://doi.org/10.1145/2532637>
- [101] Afshin Ooroofloooy and Davood Hajinezhad. 2023. A review of cooperative multi-agent deep reinforcement learning. *Appl. Intell.* 53, 11 (2023), 13677–13722. <https://doi.org/10.1007/S10489-022-04105-Y>
- [102] Anita Paas, Emily B. J. Coffey, Giovanni Beltrame, and David St-Onge. 2022. Towards evaluating the impact of swarm robotic control strategy on operators’ cognitive load. In *2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. 217–223. <https://doi.org/10.1109/ROMAN53752.2022.9900763>
- [103] R. K. Pandey. 2010. Architectural description languages (ADLs) vs UML: a review. *ACM SIGSOFT Softw. Eng. Notes* 35, 3 (2010), 1–5. <https://doi.org/10.1145/1764810.1764828>
- [104] Chris Peltz. 2003. Web Services Orchestration and Choreography. *Computer* 36, 10 (2003), 46–52. <https://doi.org/10.1109/MC.2003.1236471>
- [105] Danilo Pianini, Roberto Casadei, Mirko Viroli, and Antonio Natali. 2021. Partitioned integration and coordination via the self-organising coordination regions pattern. *Future Gener. Comput. Syst.* 114 (2021), 44–68. <https://doi.org/10.1016/J.FUTURE.2020.07.032>
- [106] Carlo Pincioli and Giovanni Beltrame. 2016. Buzz: A Programming Language for Robot Swarms. *IEEE Softw.* 33, 4 (2016), 97–100. <https://doi.org/10.1109/MS.2016.95>
- [107] Agostino Poggi, Giovanni Rimassa, and Paola Turci. 2002. What Agent Middleware Can (And Should) Do For You. *Appl. Artif. Intell.* 16, 9–10 (2002), 677–698. <https://doi.org/10.1080/08839510290030444>
- [108] M. Prokopenko. 2013. *Guided Self-Organization: Inception*. Springer Berlin Heidelberg.
- [109] Tie Qiu, Ning Chen, Keqiu Li, Mohammed Atiquzzaman, and Wenbing Zhao. 2018. How Can Heterogeneous Internet of Things Build Our Future: A Survey. *IEEE Commun. Surv. Tutorials* 20, 3 (2018), 2011–2027. <https://doi.org/10.1109/COMST.2018.2803740>
- [110] Ewaryst Rafajlowicz. 2008. Testing Homogeneity of Coefficients in Distributed Systems With Application to Quality Monitoring. *IEEE Trans. Control. Syst. Technol.* 16, 2 (2008), 314–321. <https://doi.org/10.1109/TCST.2007.903398>
- [111] Scott E. Reed, Konrad Zolna, Emilio Parisotto, Sergio Gómez Colmenarejo, Alexander Novikov, Gabriel Barth-Maron, Mai Gimenez, Yury Sulsky, Jackie Kay, Jost Tobias Springenberg, Tom Eccles, Jake Bruce, Ali Razavi, Ashley Edwards, Nicolas Heess, Yutian Chen, Raia Hadsell, Oriol Vinyals, Mahyar Bordbar, and Nando de Freitas. 2022. A Generalist Agent. *Trans. Mach. Learn. Res.* 2022 (2022). <https://openreview.net/forum?id=1ikK0kHjvj>
- [112] Pierluigi Riti. 2017. *External DSL*. Apress, 59–69. https://doi.org/10.1007/978-1-4842-3036-7_4
- [113] Pierluigi Riti. 2017. *Internal DSL*. Apress, 45–57. https://doi.org/10.1007/978-1-4842-3036-7_3
- [114] Alejandro Rodríguez, Alexander Grushin, and James A. Reggia. 2007. Swarm Intelligence Systems Using Guided Self-Organization for Collective Problem Solving. *Adv. Complex Syst.* 10, supp01 (2007), 5–34. <https://doi.org/10.1142/S021952907001069>
- [115] R. Keith Sawyer. 2003. Artificial Societies: Multiagent Systems and the Micro-Macro Link in Sociological Theory. *Sociological Methods & Research* 31, 3 (Feb. 2003), 325–363. <https://doi.org/10.1177/0049124102239079>
- [116] Ognjen Scékić, Tommaso Schiavonotto, Svetoslav Videnov, Michael Rovatsos, Hong Linh Truong, Daniele Miorandi, and Schahram Dustdar. 2020. A Programming Model for Hybrid Collaborative Adaptive Systems. *IEEE Trans. Emerg. Top. Comput.* 8, 1 (2020), 6–19. <https://doi.org/10.1109/TETC.2017.2702578>
- [117] Bento R. Siqueira, Fabiano C. Ferrari, Kathiani E. Souza, Valter V. Camargo, and Rogério de Lemos. 2021. Testing of adaptive and context-aware systems: approaches and challenges. *Software Testing, Verification and Reliability* 31, 7 (2021). <https://doi.org/10.1002/stvr.1772>
- [118] Adrian Sosic, Wasiur R. KhudaBukhsh, Abdelhak M. Zoubir, and Heinz Koeppl. 2017. Inverse Reinforcement Learning in Swarm Systems. (2017), 1413–1421. <http://dl.acm.org/citation.cfm?id=3091320>

- [119] Luca Di Stefano and Frédéric Lang. 2023. Compositional Verification of Stigmergic Collective Systems. In *Verification, Model Checking, and Abstract Interpretation - 24th International Conference, VMCAI 2023, Proceedings (LNCS, Vol. 13881)*. Springer, 155–176. https://doi.org/10.1007/978-3-031-24950-1_8
- [120] Shweta Suran, Vishwajeet Pattanaik, and Dirk Draheim. 2021. Frameworks for Collective Intelligence: A Systematic Literature Review. *ACM Comput. Surv.* 53, 1 (2021), 14:1–14:36. <https://doi.org/10.1145/3368986>
- [121] Shweta Suran, Vishwajeet Pattanaik, Ralf H. J. M. Kurvers, Carina Antonia Hallin, Anna De Liddo, Robert Krimmer, and Dirk Draheim. 2022. Building Global Societies on Collective Intelligence: Challenges and Opportunities. *Digit. Gov. Res. Pract.* 3, 4 (2022), 31:1–31:6. <https://doi.org/10.1145/3568169>
- [122] Richard S Sutton and Andrew G Barto. 2018. *Reinforcement Learning* (2 ed.). Bradford Books, Cambridge, MA.
- [123] Tadeusz M Szuba. 2001. *Computational collective intelligence*. John Wiley & Sons, Inc.
- [124] Andrew S. Tanenbaum and Maarten van Steen. 2007. *Distributed systems - principles and paradigms, 2nd Edition*. Pearson Education.
- [125] Maurice H. ter Beek and Ina Schaefer. 2023. Systems and software product lines of the future. *J. Syst. Softw.* 199 (2023), 111622. <https://doi.org/10.1016/J.JSS.2023.111622>
- [126] Yuanyuan Tian, Andrey Balmin, Severin Andreas Corsten, Shirish Tatikonda, and John McPherson. 2013. From "Think Like a Vertex" to "Think Like a Graph". *Proc. VLDB Endow.* 7, 3 (2013), 193–204. <https://doi.org/10.14778/2732232.2732238>
- [127] Vito Trianni. 2008. *Evolutionary Swarm Robotics - Evolving Self-Organising Behaviours in Groups of Autonomous Robots*. Studies in Computational Intelligence, Vol. 108. Springer.
- [128] Kagan Turner and Adrian K. Agogino. 2007. Distributed agent-based air traffic flow management. In *6th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2007)*. IFAAMAS, 255. <https://doi.org/10.1145/1329125.1329434>
- [129] Kagan Turner and David H Wolpert. 2004. A Survey of Collectives. In *Collectives and the design of complex systems*, Kagan Turner and David H Wolpert (Eds.). Springer Science & Business Media, Chapter 1.
- [130] Maarten van Steen, Guillaume Pierre, and Spyros Voulgaris. 2012. Challenges in very large distributed systems. *J. Internet Serv. Appl.* 3, 1 (2012), 59–66. <https://doi.org/10.1007/S13174-011-0043-X>
- [131] Luis M. Vaquero, Félix Cuadrado, Yehia Elkhatib, Jorge Bernal Bernabé, Satish Narayana Srirama, and Mohamed Faten Zhani. 2019. Research challenges in nextgen service orchestration. *Future Gener. Comput. Syst.* 90 (2019), 20–38. <https://doi.org/10.1016/J.FUTURE.2018.07.039>
- [132] V. Villani, B. Capelli, and C. et al. Secchi. 2020. Humans interacting with multi-robot systems: a natural affect-based approach. *Auton. Robot.* 44 (2020), 601–616. <https://doi.org/10.1007/s10514-019-09889-6>
- [133] Mirko Viroli, Giorgio Audrito, Jacob Beal, Ferruccio Damiani, and Danilo Pianini. 2018. Engineering Resilient Collective Adaptive Systems by Self-Stabilisation. *ACM Trans. Model. Comput. Simul.* 28, 2 (2018), 16:1–16:28. <https://doi.org/10.1145/3177774>
- [134] Mirko Viroli, Jacob Beal, Ferruccio Damiani, Giorgio Audrito, Roberto Casadei, and Danilo Pianini. 2019. From distributed coordination to field calculus and aggregate computing. *J. Log. Algebraic Methods Program.* 109 (2019). <https://doi.org/10.1016/J.JLAMP.2019.100486>
- [135] Pascal Weissenburger, Johannes Wirth, and Guido Salvaneschi. 2020. A Survey of Multitier Programming. *ACM Comput. Surv.* 53, 4 (2020), 81:1–81:35. <https://doi.org/10.1145/3397495>
- [136] Danny Weyns. 2020. *An introduction to self-adaptive systems: A contemporary software engineering perspective*. John Wiley & Sons.
- [137] Martin Wirsing, Matthias M. Hödlz, Nora Koch, and Philip Mayer (Eds.). 2015. *Software Engineering for Collective Autonomic Systems - The ASCENS Approach*. Lecture Notes in Computer Science, Vol. 8998. Springer. <https://doi.org/10.1007/978-3-319-16310-9>
- [138] Martin Wirsing, Matthias M. Hödlz, Mirco Tribastone, and Franco Zambonelli. 2011. ASCENS: Engineering Autonomic Service-Component Ensembles. In *Formal Methods for Components and Objects, 10th International Symposium, FMCO 2011, Revised Selected Papers (LNCS, Vol. 7542)*. Springer, 1–24. https://doi.org/10.1007/978-3-642-35887-6_1
- [139] David H. Wolpert and Kagan Turner. 1999. An Introduction to Collective Intelligence. <https://doi.org/10.48550/ARXIV.CS/9908014>
- [140] Zena Wood and Antony Galton. 2009. A taxonomy of collective phenomena. *Appl. Ontology* 4, 3–4 (2009), 267–292. <https://doi.org/10.3233/AO-2009-0071>
- [141] Michael J. Wooldridge. 2009. *An Introduction to MultiAgent Systems, Second Edition*. Wiley.
- [142] Hansong Xu, Wei Yu, David W. Griffith, and Nada Gomie. 2018. A Survey on Industrial Internet of Things: A Cyber-Physical Systems Perspective. *IEEE Access* 6 (2018), 78238–78259. <https://doi.org/10.1109/ACCESS.2018.2884906>
- [143] Yaodong Yang. 2021. *Many-agent reinforcement learning*. Ph.D. Dissertation. UCL (University College London).
- [144] Yichen Yang, Jeevana Priya Inala, Osbert Bastani, Yewen Pu, Armando Solar-Lezama, and Martin C. Rinard. 2021. Program Synthesis Guided Reinforcement Learning for Partially Observed Environments. In *Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS 2021*, 29669–29683.
- [145] Yaodong Yang, Rui Luo, Minne Li, Ming Zhou, Weinan Zhang, and Jun Wang. 2018. Mean Field Multi-Agent Reinforcement Learning. In *Proceedings of the 35th International Conference on Machine Learning, ICML 2018 (Proceedings of Machine Learning Research, Vol. 80)*. PMLR, 5567–5576. <http://proceedings.mlr.press/v80/yang18d.html>
- [146] Yaodong Yang and Jun Wang. 2020. An Overview of Multi-Agent Reinforcement Learning from Game Theoretical Perspective. *CoRR* abs/2011.00583 (2020). arXiv:2011.00583 <https://arxiv.org/abs/2011.00583>
- [147] Dayong Ye, Minjie Zhang, and Athanasios V. Vasilakos. 2017. A Survey of Self-Organization Mechanisms in Multiagent Systems. *IEEE Trans. Syst. Man Cybern. Syst.* 47, 3 (2017), 441–461. <https://doi.org/10.1109/TSMC.2015.2504350>
- [148] Peijun Ye, Yuanyuan Chen, Fenghua Zhu, Yisheng Lv, Wanze Lu, and Fei-Yue Wang. 2022. Bridging the Micro and Macro: Calibration of Agent-Based Model Using Mean-Field Dynamics. *IEEE Trans. Cybern.* 52, 11 (2022), 11397–11406. <https://doi.org/10.1109/TCYB.2021.3089712>
- [149] Chas Yu, Akash Velu, Eugene Vinitsky, Jiaxuan Gao, Yu Wang, Alexandre M. Bayen, and Yi Wu. 2022. The Surprising Effectiveness of PPO in Cooperative Multi-Agent Games. In *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022*, NeurIPS 2022. http://papers.nips.cc/paper_files/paper/2022/hash/9c1535a02f0ce079433344e14d910597-Abstract-Datasets_and_Benchmarks.html
- [150] Zequn Zhang, Dunbing Tang, and Qingwei Nie. 2021. Research on Workers Integration in Smart Factories With Multi-Agent Control System. *IEEE Access* 9 (2021). <https://doi.org/10.1109/ACCESS.2021.3115339>