Multi-scale Feedbacks for Large-scale Coordination in Self-* Systems

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***Abstract*—Multi-scale structures, or hierarchies, are prevalent in large-scale dynamic systems, from inert matter to living and artificial systems, and systems-of-systems. Yet, a general theory helping to understand and develop multi-scale systems is still missing. This paper identifies common design aspects and variants, and synthesises them via a novel design pattern – *Multi-Scale Feedbacks* – to help adaptive coordination in large-scale systems. It also suggests relations between design choices and qualitative properties. The proposed pattern was distilled from a cross-domain study, including particle physics, molecular biology, neuroscience, insect and human organisations, ecosystems, autonomous control and systems-of-systems.**

***Index Terms*—multi-scale feedbacks, hierarchy, adaptive control, large-scale coordination, design pattern, robustness**

I. Introduction

Multi-scale structures, or hierarchies, are prevalent in large-scale systems, from inert matter to organisms, artificial systems and systems-of-systems. Here, system behaviour impacts that of its parts (top-down), and vice-versa (bottom-up). While a popular research topic – e.g., hierarchic control [1], holarchy [2], [3], multi-scale systems [4], micro-macro dynamics [5], or multi-level composition [6] – the diversity of domain-specific studies makes it difficult to grasp the key concepts behind the success of hierarchic designs. This hampers their cross-domain reusability for analysing and developing self-* systems.

This paper aims to identify the key design principles common to hierarchical self-* systems. We focus on hierarchies that achieve *large-scale coordination* – i.e. organising system sub-processes to reach a shared goal, robustness and survival. This involves a particular kind of *inter-level feedback*, via multi-source data-collection and aggregation (bottom-up) and collective control and adaptation (top-down). We exclude hierarchies that lack inter-level feedback – ranking (e.g. best universities), authority (e.g. top-down order), ontology (e.g. evolutionary tree), or transport (e.g. blood circulation).

Bottom-up aggregation and top-down adaptation rely on information flows between hierarchical levels. Thus, coordination scalability is limited by the (information) *communication capacity* among coordinated sub-processes, and *processing capacity* of sub-processes [16]. When reaching capacity, a coordination process may [9], [11]: a) *self-optimise* its efficiency; b) *self-replicate* and parallelise processing; or, c) *collapse*. When parallel coordination occurs (b), it may require higher-level coordination, with its own capacity limit, leading to a recursive scalability problem, and a growing hierarchy.

Higher-level coordination is only viable if lower processes present themselves as relatively robust entities, with simplified sensing and control interfaces. Otherwise, exposing higher levels to low-level intricacies would require increasing capacity, hence limiting scale [2]. Thus, higher coordination must be able to rely on *abstracted information* about lower self-* processes, and to control these via *abstracted commands*.

We focus on *multi-scale feedbacks* (Fig. 1), where 'higher' feedbacks operate at a more abstract level than 'lower' ones. We identify various implementation forms under which higher entities, or *macro-features*, may occur: 1) *exogenous*, distinct entities (e.g. army command); 2) *composite* micro-entities (e.g. cell membrane), and 3) *micro-distributed* across micro-entities (e.g. social norms). We also aim to analyse the ensuing qualitative properties – e.g. sensitivity, reactivity, robustness, adaptability and scalability. These initial findings are synthesised via a novel *design pattern* [28] – *Multi-Scale Feedbacks* – including its entity types, roles and relations (III, IV); possible variants (V); and application examples (VI).

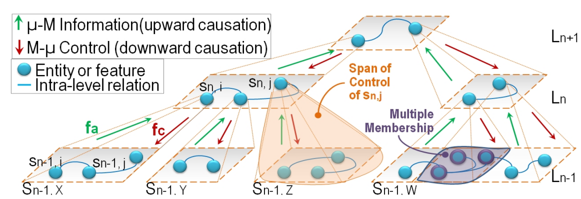

Fig. 1. Overview of Multi-Scale Feedbacks

This differs from autonomic patterns for distributing MAPE-K functions [26] [27] and may adopt bio-inspired patterns [25] to spread and aggregate information. Our proposal generalises from autonomic architectures [32] and applications [33], [31]. Previously, we proposed a hierarchical architecture [36] featuring abstraction, encapsulation and time-tuning; illustrated in [37] via a hierarchical cellular automata simulator. Here, we focus on inter-level feedbacks – design features, variants and qualities. We adopt principles from previous *hierarchy theories*, including Allen's multi-scale observer perspective [7], Simon's [2] and Koestler's [3] recursively encapsulated hierarchies, and Pattee's cross-domain hierarchy examples [4]. Hence, our proposal builds on existing work, and aims to bridge it under a unified framing; advancing towards a shared language and analysis framework for multi-scale systems.

II. Related Work

A. Software Engineering

Multi-Scale Feedbacks includes control architectures proposed in Autonomic [32], Organic [30] and Self-Aware Computing [29]. *Exogenous* designs define macro-entities as higher controllers [33], layers [32], [31], or contextual entities [22]. In *composite* designs, higher controllers (macro) encapsulate lower ones (micro) [35]; similarly to component-, service- or agent-based composition [34], or problem decomposition [38]. In *micro-distributed* designs, macro-entities are spread across micro-entities, coordinated via peer-to-peer schemes [23].

B. Control Engineering

Hierarchical Control Theory aims to decompose control problems into sub-problems and recompose sub-solutions into an optimal controller. Hierarchical levels differ in their planning and execution time horizons, or in their rationality ("increasing precision with decreasing intelligence") [40]. Hierarchical Perceptual Control Theory (HPCT) defines multi-scale goal-driven controllers (*exogenous*), with lower perceptions feeding into higher ones, and higher feedbacks setting goals for lower ones [41]. The Operator Theory[1] defines hierarchical 'levels' based on *closure*, or closed loops, where 'basic units' build higher units, e.g. quarks, atoms, cells (*composites* in our case); and groups, e.g. swarms (*micro-distributed*).

C. Anthropology and Sociology

Extensive anthropological studies [9], [10], [11], [12] link the communication scale in human groups to their organisation types. The key factor is 'communication stress' [16], within or between group members, leading to various hierarchies: no hierarchy in small groups to avoid overheads (e.g. < 6 members [11]); 'horizontal' hierarchy at mediate scales to deal with 'scalar stress' [11] (e.g. 'knowledge aggregation' in Ancient Athens [13]) – *micro-distributed* feedbacks; and 'vertical' hierarchies at larger scales to improve reactivity and convergence [10] – *exogenous* feedbacks. Further design insights include: viable control scopes (e.g. 3-5 subordinates [14]); and the relation between a hierarchy's height, and, more specialisation at lower levels [10] and power at top levels [15].

D. Neuroscience

Several brain studies discuss neocortex modularity [18], and cortex scaling [19]. The Human Brain Project[2] offers further insights into multi-scale modularity [17]; hierarchical decision-making [20]; and spatio-temporal neural hierarchies for more robust, less computational, controlled behaviour [21].

III. Generic Model of Multi-scale Systems

We model a self-* system as a set of *processes* P (Fig. 2), which can represent self-* *entities* $E = \{e_x | x = 1..M\}$ and *relations* $R = \{r_{e_x,e_y} | e_x, e_y \in E, x \neq y\}$; hence $P = E \cup R$. A relation can be either an *association* (e_x communicates with e_y) or a *composition* (e_x contains e_y).

[1]https://www.theoperatortheory.info – accessed Feb 2019

[2]www.humanbrainproject.eu

We adopt an *Observer-Observable* approach, where e_x is *Observable* if it has a *feature* $s_{x,i}$ that can be observed by other entities; and e_y is an *Observer* of e_x if it can observe $s_{x,i}$. An observation means that a change in the observed feature $s_{x,i}$ at time t leads to a change in the observer entity e_y at $t + k$, $k > 0$. Active *sensing* at higher levels merely consists of passive change-transmission processes at lower levels. To simplify, we use notation s_i for both e_x and $s_{x,i}$; $s_{n,i}$ for s_i at level L_n, $n = 1..N$; and $s_{n,i,t}$ for an observation at time t.

Considering a macro-feature $s_{n,i}$ (at L_n), we distinguish three kinds of micro-entity sets (at L_{n-1}):

- *input micro-entities* $\mu_{in}(s_{n,i})$ leading to $s_{n,i}$ (bottom-up);
- *output micro-entities* $\mu_{out}(s_{n,i})$ impacted by feedback from $s_{n,i}$ (top-down);
- *composing micro-entities* $\mu_{cmp}(s_{n,i})$ forming the substrate entity on which the macro-feature $s_{n,i}$ is formed.

These micro-entity sets can overlap to various extents, resulting in different macro-entity types (sec. V). $\mu_{in/out}(s_{n,i})$ represents both the micro-inputs and -outputs of $s_{n,i}$.

IV. Key Design Aspects of Multi-scale Feedbacks

A. Design Pattern Overview

The Multi-Scale Feedbacks pattern addresses the *problem* of *large-scale coordination*, via a *solution* based on *hierarchical feedback-loops*, operating at increasing abstraction levels, each one exposed to a *specific context* (application-dependent). We identify the pattern's key design aspects (IV.B-F) and variants (V), grounding them in cross-field examples (VI A-H) and discussing their qualitative properties (VI-I):

- *sensitivity* – the magnitude of change causing a reaction;
- *reactivity* – the speed of reaction;
- *robustness* – resistance to failure, overload, perturbations;
- *adaptability* – internal alteration in reaction to change;
- *scalability* – viability with increasing coordination load;
- *extensibility* – continuous growth and alteration.

B. Micro-to-Macro Abstraction

Micro-to-macro information abstraction leads to the formation of a macro-feature $s_{n+1,i}$ (at L_{n+1}) from a set of micro-features $S_{n,X}$ (at L_n), Fig. 1. Given $R_{S_{n,X}}$ the set of relations among features in $S_{n,X}$, we define an *abstraction function*, f_a:

$$s_{n+1,i,t+k} = f_a(S_{n,X,t}, R_{S_{n,X,t}}), \quad k > 0 \tag{1}$$

Also (Cf. III), $\mu_{in}(s_{n+1,i,t+k}) = S_{n,X,t}$. Abstraction ($f_a$) can take various forms – e.g., average, model, filter, boolean, dimension reduction, max, or voting. Statistic functions help robustness, while modelling preserves sensitivity and reactivity. In all cases, f_a 'loses' information (from L_n to L_{n+1}), hence limiting complexity (at L_{n+1}).

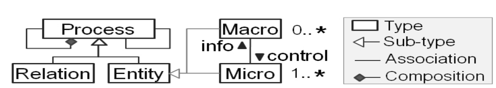

Fig. 2. Types Model for Multi-Scale Systems

Information abstraction is also referred to in the literature as *coarse graining*, *aggregation*, or *upward causation* [5].

C. Macro-to-Micro Feedback

We define a *feedback function* f_c to characterise change transmission from macro- (L_{n+1}) to micro-features (L_n):

$$S_{n,X,t+l} = f_c(s_{n+1,i,t}, S_{n,X,t}), \quad l > 0 \tag{2}$$

Hence, micro-features $\mu_{out}(s_{n+1,i})$ depend on a macro feature $s_{n+1,i}$, and on their previous state. If $\mu_{out}(s_{n+1,i}) \equiv \mu_{in}(s_{n+1,i})$, then $s_{n+1,i,t} = f_a(S_{n,X,t-k}), k > 0$.

Negative feedbacks stabilise micro states; positive feedbacks escalate changes; and adaptive feedback combines the above [1]. The *timing* between macro-state formation and subsequent micro-state adaptation impacts system stability (IV-D).

Macro-to-micro feedback is also referred to in literature as *command & control*, *fine-graining*, or *downward causation* [5].

D. Time Scales

Feedback loops at different levels operate at different time scales, impacting system stability. They may be *synchronised* (upward aggregation and downward commands fit within a single cycle); yet most hierarchies are *asynchronous* (executing in parallel). To reach stability, higher levels typically execute slower than lower levels. Still, when higher feedbacks are too slow relative to fast low-level changes, system viability may be jeopardised. Conversely, systems that seek instability practice inverse timing scales. When inter-level time scales highly differ, levels can be considered in (semi-)isolation, facilitating complexity management. Still, slow macro-phenomena may pass undetected at fast micro-levels, which may fail to adapt.

E. Topology

Several topological characteristics are relevant here (Fig. 1).

1) Span of Control: the number of micro entities mapped to each macro entity $|\mu_{in/out}(s_{n,i})|$. This impacts reactivity, sensitivity and robustness (e.g., teams of 3-5 members [11]).

2) Feedback Cross-Influence: a macro-feature $s_{n,i}$ impacts micro-features outside its inputs, $\mu_{in}(s_{n,i}) \neq \mu_{out}(s_{n,i})$ (e.g., a political party's opinions influencing non-party members).

3) Multi-Membership: micro-entities related to several macro-features, $\mu_{in/out}(s_{n,i}) \bigcap \mu_{in/out}(s_{n,j}) \neq \emptyset, \quad i \neq j$. This breaches encapsulation (IV-F) and may cause conflicts.

4) Verticality: the number of hierarchy levels N, typically increasing with system size and coordination load [14].

F. Partial Encapsulation

Encapsulation limits and filters exchanges between external entities and micro-entities 'contained' within macro-entities. It can be achieved via a spatio-temporal border or a communication border (structural vs functional closure in [8]). Encapsulation relates to the above design aspects: a) its occurrence leads to information abstraction and different time scales between contained and external entities; b) the occurrence of information abstraction and different time scales between entity sets leads to an inside-outside separation, hence a border, between them. Encapsulation is key to modularity and reusability, limits external perturbations and ripple effects. It enhances system robustness, adaptability, extensibility and scalability. Observers perceive encapsulated micro-entities as one macro-entity, with stable macro-features (hiding micro-details and instabilities); and can build upon it. This helps increase system complexity with limited required capacity.

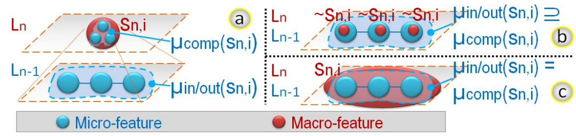

Fig. 3. Macro-types: a) exogenous; b) micro-distributed; c) composite

V. Macro-feature Design Types

We distinguish three macro-feature types – *exogenous*, *micro-distributed* and *composite* (Fig. 3) – providing similar feedbacks, yet via different substrates and with different properties. Also, micro-entities related to a macro-feature – i.e. μ_{in}, μ_{out} or μ_{comp} – may be *loosely-coupled* or *tightly-coupled*, depending on their interrelations' relative changing frequency (e.g. loose organisation members vs tight organism cells).

Exogenous, or ***role-playing*** macro-features form within stand-alone entities, observable separately from their input micro-entities: $\mu_{in/out}(s_{n,i}) \neq \mu_{comp}(s_{n,i})$. They can be of the same kind as their in/out micro-entities (e.g., neurons in a nervous system), or of different kinds (e.g. pheromone trails in ant colonies). They have an *association* relationship with their in/out micro-entities; which can be tightly-coupled (e.g. neurons) or loosely-coupled (e.g. ants).

Micro-distributed macro-features are distributed across their input micro-entities: $\mu_{in/out}(s_{n,i}) \subseteq \mu_{comp}(s_{n,i})$ (e.g. culture, residing within every society member and artefacts). They have association relations with their in/out micro-entities.

Composite macro-features form within entities that are composed of their input micro-entities, without which they cannot exist: $\mu_{in/out}(s_{n,i}) = \mu_{comp}(s_{n,i})$ (e.g., a cell composed of molecules, composed of atoms, electrons and quarks). They *encapsulate* their in/out micro-entities (composition relationship); which are, at least partially, tightly-coupled.

VI. Examples

A. Particle and Molecular Physics

Atom robustness and chemical properties (macro) enable their use as building blocks for larger-scale systems. They are composed of entities (particles) and relations (forces), Cf. Fig. 2. Quarks held together by the strong nuclear force form hadrons – protons and neutrons – which form atomic nuclei. These have positive electric charge (macro), which keeps negative electrons around them, via the electromagnetic force, forming atoms. Different (micro) compositions lead to atoms with various chemical properties (macro), able to form diverse molecules. Interestingly, atom scalability is limited (e.g. unstable over 100 protons); and macro-to-micro impact seems essential (e.g. quarks do not exist in free form).

B. Unicellular Organisms

A cell's autopoietic processes (micro) maintain its membrane (macro), which protects internal processes (micro) from the environment (i.e. *composites*). Process coordination via chemical diffusion has limited capacity – most unicellulars are microscopic, with a few exceptions (e.g., Caulerpa seaweed reaches up to 3m, yet with several coordinating nuclei; Thiomargarita bacteria is non-motile, up to 0.75mm, yet including large storage vacuoles to avoid starvation). As multiple cells come together, coordination require more efficient, scalable processes (e.g. multi-layer neural systems [24]).

C. Neural Networks – the Visual Cortex

The visual cortex is a multi-scale adaptive system, with 5 levels corresponding to distinct cortical areas [44] [45] [46]. Processing from retina involves two pathways (micro-macro abstraction): i) ventral pathway, for progressive object recognition (lines, edges, shapes, etc); and ii) dorsal pathway, for object spatial location. Abstraction (f_a) is threshold-crossing, with higher neurons firing when sufficient lower neurons fire. The threshold depends on adaptive neuron sensitivity (learning). Lower levels are larger than higher ones (V1 and V2 contain ≈70% of visual cortex neurons) pointing to upward aggregation and a wide basal control scope. The neuron receptive fields (regions where stimulus modifies firing) get larger at higher levels (x2 at V2 than at V1), suggesting increasingly distributed input collection towards the top. Structurally, this is an *exogenous* system (neurons playing macro roles), relatively tightly-coupled, and non-encapsulated.

Object recognition triggers two feedbacks (macro-micro): i) control of neurons outside the visual cortex ($\mu_{in} \neq \mu_{out}$), e.g. eye movement to focus on an interesting spot; and ii) contrast adaptation, where visual cortex neurons ($\mu_{in} = \mu_{out}$) filter-out unchanging background information and focus on fore-front fast-moving objects (gain or danger) [47]. These feedbacks are highly sensitive and reactive, which is crucial for survival. A third, relatively slower feedback concerns perceptual learning [48] via the neurons' memorising capacity. It facilitates pattern-recognition, adapting and optimising for specific circumstances. As neurons do not store information indefinitely, it also allows re-adaptation to new environments.

D. Social Insects – Ant Colonies

Ant colonies are multi-scale adaptive systems [49] [50] [51], with feedbacks going from ants (micro) to the colony (macro) and back to ants (micro). Yet, "the colony does not depend on the transmission of information up and down chains of command before decisive local action can be taken" [51]. Colonies are loosely-coupled (ants move freely) and non-encapsulated. We discuss two feedback types. The first is *micro-distributed* and relies on the detection of macro-patterns by each ant, through repeated antennae interaction with other ants (i.e. mass communication [49]). This maintains division-of-labour within a colony, as each ant determines which tasks are needed by aggregating information on which task was performed by other ants encountered (e.g. via temperature and humidity of antennae); and adapting their tasks accordingly. Here, information patterns computed by an ant are the macro-feature μ_{comp}, with μ_{in} including encountered ants and $\mu_{out} = \mu_{comp}$ the ant's behaviour adaptation.

The second feedback type is *exogenous*, using the external environment to aggregate information (stigmergy). Pheidole ants use this to maintain division-of-labour between major and minor ants [49]. Majors have an aversion to chemicals released by minors. When minors perform nest-related tasks, majors stay away. When minors vanish (e.g. disease), majors move in and perform those tasks. The aggregated chemical is the macro feature, with minors as μ_{in} and majors as μ_{out}.

In both cases, f_a and f_c are statistical, computed by each ant, leading to viable probabilistic behaviour within the colony. As ants only compute a few signals and perform few actions (20-40 depending on species), and as none of the macro-types are subject to capacity overload, ant colonies are extremely scalable (up to millions or billions of ants). Still, macro-features have limited capacity (e.g. chemicals reach maximum concentrations and dissipate), avoiding escalating feedbacks.

E. Socio-technical Organisations – Army Platoons

The Reference Model Architecture For Unmanned Vehicle Systems described by NIST [42] gives the structure of an army organisation in which un/manned vehicles coordinate to achieve goals. It describes human control at the highest level (battalion) and transitions to autonomous control at the lower levels. Tasks are decomposed at each level, limiting each node's control scope, and hence computing and memory load. Each battalion controls 4 companies, each with 3-4 platoons, each with 10 vehicles (autonomous or 2-6 soldiers). This ensures high sensitivity, reactivity, robustness and adaptability.

These are *exogenous* hierarchies, commanders playing macro-roles; and non-encapsulated (above human and vehicle levels). Abstraction f_a provides models of the environment, status and goals – e.g., multi-scale maps, with 100km range and 30m resolution for battalions (L_8), and 500m range with 4m resolution for vehicles (L_4). Feedback (f_c) consists in command signals passed top-down with increasing detail. E.g., a battalion commander determines vehicle way-points, a vehicle controller determines paths, and low level controllers determine steering and acceleration profiles. This allows each micro level to adjust its objective to the macro objective without information overload. Time scales are also well-defined, with lower levels (L_{n-1}) acting 5-10 faster than higher levels (L_n). E.g., battalions L_8 plan for 24h, and update them every 5h; companies L_4 plan for 5h, with 25min updates; and the servo level L_1 plans for 50ms, executed every 5ms.

F. Culture – Social Norms Formation and Evolution

[43] provides a small-scale model for cultural norm formation and evolution. It studied the tipping point for changing an established convention based on the number of holders of an alternative view. Randomly-paired subjects were asked to label an image. Each subject was rewarded for assigning the same label and punished otherwise. Once a social norm

was established, a committed subgroup was brought-in, always using one alternative label, ignoring rewards or punishments. Results found that 15%-35% of inflexible individuals sufficed to change the previous convention to the alternative one. Here, norms (macro) are *micro-distributed* across group members, with respective control scopes changing after each interaction. This hierarchy has no global goal, only self-interested individuals. Abstraction (f_a) occurs as each individual estimates the others' views; consequently changing their behaviour (f_c). As the alternative sub-group is not adaptive, their view becomes the only convergence point. System reactivity depends on individual adaptability and exposure to alternative norms.

G. Eco-systems – Forests

In forests, tree growth (micro) creates spatial patterns (macro) at the patch level, which affect tree growth (micro) by shaping light-availability [52]. These are feedbacks with *composed* macro-types ($\mu_{in} = \mu_{out} = \mu_{comp}$), tightly-coupled, non-encapsulated, detail-sensitive f_a, and dependent on initial conditions (species) [53]. Another feedback involves soil resource availability (e.g. nutrients). It is *exogenous*, with f_a aggregating nutrient prosumption of all trees [52].

The overall dynamics follows an 'adaptive cycle' pattern (Cf. Holling's panarchy theory [54]): forest patch configurations stabilise over long periods via relatively fast adaptive feedbacks; then get disrupted by slower negative feedbacks (e.g. the domination of a fire-prone species leading to fire), leading to short-term forest patch reconfiguration (i.e. new combination of species); followed by another stable period. Unlike organisms, eco-systems do not maintain a particular goal and may change dramatically between cycles.

H. Socio-Technical Systems-of-Systems – Energy Grids

Energy systems are governed by two major feedback types, each operating at multiple scales: i) slow – institutional decisions, plant construction, infrastructure [55] [56]; and ii) fast – grid operation to balance prosumption [35]. In institutional feedbacks, f_a produces multi-scale system models (e.g. production and CO_2 emission of plants, technology groups, and grid). Decisions are encoded as laws and regulations f_c (e.g. high CO_2 may prompt governments to shift production from coal plants to solar and wind farms). In prosumption feedbacks, f_a provides multi-scale prosumption aggregates (e.g. neighbourhood, region, country), helping robustness and scalability. f_c consists in top-down adjustment commands for flexible plants, ranging from milliseconds, to seconds, hours and days. While institutional feedbacks adjust high-level system goals and infrastructure, prosumption feedbacks maintain those goals using the infrastructure. All feedbacks are *exogenous*, relatively tightly-coupled, and non-encapsulated.

I. Discussion

Table I summarises the main design choices for the above examples of multi-scale feedbacks. Table II links qualitative properties to design choices in the examples.

Reactivity depends on the *input stress*, or capacity load, of macro entities and micro-macro communication. It can be improved by: narrow control scopes (e.g. army); highly abstracted f_a (e.g. prosumption aggregates; visual cortex attention filtering); low verticality before feedback (army, cortex, ants); resource provisioning (e.g. grid management, cortex).

Example	**Macro**	**f_a & f_c**	**Couple**	**Encaps.**
atom	composite	detail-sensitive	tight	yes
cell	composite	statistical	both	yes
cortex	exogenous	threshold	$\approx$ yes	no
ant patterns	micro-distr.	statistical	no	no
forest patches	composite	detail-sensitive	yes	no
forest nutrients	exogenous	statistical	yes	no
army	exogenous	models	no	both
social norms	micro-distr.	statistical	no	no
grid management	exogenous	statistical	$\approx$ yes	no
grid institutions	exogenous	models	no	no

TABLE I
EXAMPLES DESIGN OVERVIEW

Qualitative property	**Design properties**	**Examples**
reactivity	low decision verticality & low capacity stress	army, cortex energy manag.
sensitivity	detail-sensitive f_a & f_c	energy instit.; army, forest
slow adaptation	shallow verticality	ants, norms
fast adaptation	deep verticality	army, cortex
robustness (resilience & stability)	heterogen., stats. f_a, redund., encaps., adaptive feedback	ants, cortex, cell, atom
extensibility & evolvability	micro-stability for new micro- /macro-types	molecules, multicellulars
scalability	limit capacity stress; abstract, parallelize, delegate	all

TABLE II
STRUCTURAL AND QUALITATIVE PROPERTIES

Sensitivity requires detail-preserving abstractions f_a (e.g. models), increasing input load on macro-entities (e.g. army commanders). Tall narrow hierarchies offer a compromise (e.g. army), yet using more resources – i.e. many levels with parallel feedbacks and small control scopes, faster at the base than at the top. Shallower hierarchies offer slower global adaptation with fewer resources (e.g. ant colonies, social norms).

Robustness relies on heterogeneity (avoids mass failure and promotes diverse adaptation), encapsulation (limits environment uncertainty and chain reactions), redundancy (overcomes partial failures and overloads) and stability (deals with perturbations via combined positive and negative feedbacks [58]). In ant colonies, worker redundancy increases with colony size [50], improving task completion and colony effectiveness [51]. Neural networks can generate a behaviour via diverse paths [21], redundancy increasing with scale and improving robustness exponentially. Still, redundancy is costly and sometimes replaced with higher internal flexibility (e.g. adaptable plants in energy grids; totipotent ants in small colonies).

Extensibility and *evolvability* rely on the macro-stability ensured by encapsulated, tightly-coupled micro-entities (e.g. molecules from atoms, organisms from unicellulars, societies from individuals). *Scalability* hinges on the ability to avoid capacity overload at the macro-level (e.g. inhibiting inputs, optimising internally, employing redundant resources).

VII. Conclusions and Future Developments

This paper identified key design aspects and variants of multi-scale feedback systems in an effort to provide a common cross-domain language and theory for understanding and developing such systems. These findings were distilled from an extensive cross-domain study of hierarchical feedback systems. The contribution consisted in defining a generic design pattern, Multi-Scale Feedbacks, summarising our findings in a reusable manner. The pattern's occurrence across a wide range of real examples supports its viability. We also suggested several links between hierarchical design choices and ensuing qualitative properties. Future work will solidify these links and advance towards a theory of multi-scale feedbacks.

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