Life as a Cyber-Bio-Physical System

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Abstract The study of living systems—including those existing in nature, life as it could be, and even virtual life—needs consideration of not just traditional biology, but also computation and physics. These three areas need to be brought together to study living systems as cyber-bio-physical systems, as *zoetic systems*. Here I review some of the current work on assembling these areas, and how this could lead to a new Zoetic Science. I then discuss some of the significant scientific advances still needed to achieve this goal. I suggest how we might kick-start this new discipline of Zoetic Science through a program of Zoetic Engineering: designing and building living artefacts. The goal is for a new science, a new engineering discipline, and new technologies, of zoetic systems: self-producing far-from-equilibrium systems embodied in smart functional metamaterials with non-trivial meta-dynamics.

1 Introduction

It is certainly the case that "Nothing in biology makes sense except in the light of evolution" [1]. Although this evolutionary light is necessary, it is by no means sufficient for such sense making. In order to make sense of life,[1] and of living systems, we also need the light of physics and computing.

Here I survey the advances made in bringing these lights of computing and physics to bear on living systems and suggest a new Zoetic Science that fully integrates these

[1]I will not get into definitional questions of what makes systems 'really' 'alive' [2]. However, consider "living organisms are those material systems that are able to manipulate information so as to produce unexpected solutions that enable them to survive in an unpredictable future", and "life as a process that enables material systems to manipulate, create, and accumulate information" [3].

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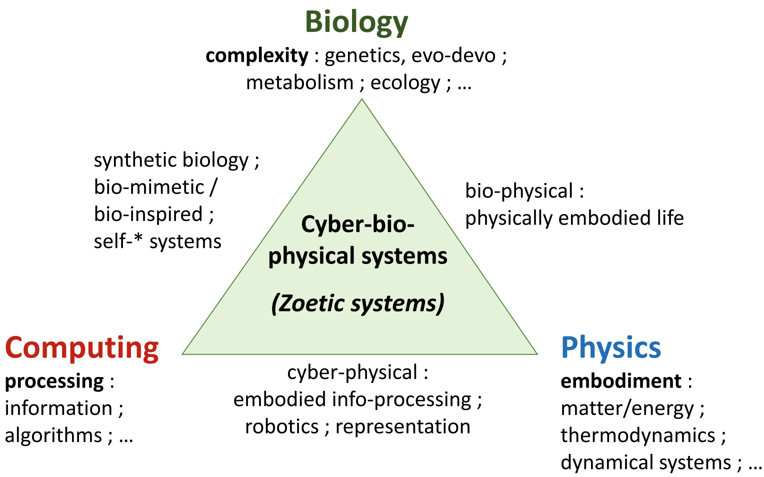

Fig. 1 The triangle of life, combining biology, computing, and physics in cyber-bio-physical systems

components. I suggest the way forward to developing this science is through Zoetic Engineering case studies, with an example of starting from a basis of swarm robotics and morphogenetic engineering.

2 The Triangle of Life

I argue that the science and engineering of life, of living systems, requires more than the study of biology alone. Biology as it stands today studies *life as we know it* on Earth; exobiology studies (currently hypothetical) life in the rest of the Universe. Artificial Life (ALife) studies *life as it could be* more generally [4], including theoretical, computational, and experimental approaches, and with consideration of fields and aspects beyond that of core biology itself, particularly (i) the physical embodiment of the living systems, and (ii) the informational and computational aspects of living processes. Even the study of life as we know it needs to include these physical and computational aspects for a fully developed approach. I encapsulate these aspects conceptually in Fig. 1.

The vertices in Fig. 1 represent the individual fields that together are needed to capture the complexity of living systems. In Sects. 2.1–2.3, I pick out a few aspects of each discipline that are most relevant to the topic of life and life-like systems. The edges in Fig. 1 represent pairwise cross-disciplinary interactions between the individual fields. In Sects. 2.4–2.6, I pick out a few relevant aspects of these interactions. The face in Fig. 1 represents the combination of all three aspects brought together as cyber-bio-physical systems; see Sect. 2.7.

2.1 B: Biology

Biology is a science of complexity, the complexity of the living world. Since it has only one instance for study (life on earth), it typically does not address questions of what is necessary for life, and what is merely contingent of its realisation on this planet, and given its specific evolutionary history. One of the goals of the field of ALife is to broaden this scope.

The topics of biology can be broken down into four approximate levels (below). These levels are often studied in isolation, although cross-level effects, such as evo-devo (the interaction of evolutionary and developmental processes) and evolutionary ecology, are considered. One key constraint of natural living systems is that individuals and all their evolutionary ancestors are viable throughout their processes of birth, maturation, and reproduction: there is a continuous chain of life.

The entire subject is incredibly complex, and there are many exceptions to any rule; specific models tend to be preferred over abstract approximate ones [5].

Substrate. The lowest level considered is the substrate of biomolecular materials and processes. This includes biochemical processes of manipulation and construction of the substrate: metabolism (catabolism, the breaking down of large molecules and releasing of energy, and anabolism, the building up of more complex molecules, using energy). It also includes reproduction and replication of the substrate.[2] This is based in the field of molecular genetics, of the 'control program' of transcription, translation, and replication of DNA.

Individual. The individual level is that of a single whole organism. This includes sensing, (re)acting, moving, adaptation, and learning, including neural cognition (in animals) and adaptive immunity (in vertebrates). For multicellular organisms, it includes the process of ontogeny/development/growth from single cells to mature organisms to death, again mediated by the genetic program. There is no single solution; organisms adapt to and are shaped by their context or environment:

> Other minds, other worlds from the same monotonous and inexpressive chaos! My world is but one in a million alike embedded, alike real to those who may abstract them. How different must be the worlds in the consciousness of ant, cuttlefish, or crab! [6, Chap. IX]

Population. This is the species level. It includes evolution: how the genetics changes. It covers populations of individuals both in terms of belonging to a species, and also as 'superorganisms' (for example, social insects) acting as a higher level individual. It includes ideas of major transitions in complexity [7, 8], open-endedness [9, 10], and goes meta with evo-evo (the evolution of evolutionary processes) [11].

System. The highest level considered is of an ecosystem of multiple species, and their interactions with each other (such as competition for shared resources, predation and

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[2] A distinction is drawn between reproduction (of the physical machinery, the cell) and replication (of the informational content, the DNA) [3]; many abstract models (for example, basic evolutionary algorithms) however do not separate these processes.

food webs, cooperation, and symbiosis) and with the physical environment (exploiting and creating niches). Ecosystems exist on multiple scales, from communities to the entire biosphere.

2.2 P: Physics

Physics is a science of (relative) simplicity, that of matter and energy behaving in space and time, of embodiment.

2.2.1 Matter

Matter forms the substrate material of living organisms and of their physical environment. The biological processes are embodied in the physical material and are subject to its constraints (the processes it limits) and its opportunities (the processes it supports, enables, or performs). For life on earth, many of these processes are chemical in nature and non-ergodic.

This substrate material occurs in highly evolved complex structures and molecules that are not observed in non-living matter. The existence of suitably complex molecules can be used as a biosignature, either directly of the evolved life itself or indirectly of an artefact engineered by evolved life [12]. (Free oxygen is also considered to be a sign of life.) As well as providing the substrate of biological processes (metabolism, growth, reproduction, etc.), the matter is used to store the energy (typically as chemical energy) needed to drive those processes.

2.2.2 Energy and Entropy

Thermodynamics is the physics of energy conservation and entropy production. Energy is needed to drive biological processes; the flux of sunlight can be accessed directly by plants; this flux needs to be converted to chemical energy for use by other organisms. Chemical energy can be stored, which allows for energy use when the flux is not available (for example, in shadows and caves, or at night), or not instantaneously sufficient for certain processes.

Energy flux is lost to the system if not used or stored; matter is constantly recycled in ecosystems [13]. Energy is conserved overall, but it gets degraded from free energy to forms that cannot be used to do work: entropy increases. Life, despite being able to locally decrease entropy by creating order and structure, nevertheless overall increases the rate of entropy production [13]. As Russell [14] puts it:

> the *raison d'être* of life is to dissipate energy and produce heat and waste, the exhausts from biosynthesis: life is an entropy generator. The more entropy an organism can generate, the more successful it is: for a while.

2.2.3 Time and Dynamics

Physical systems are often modelled as dynamical systems: a set of differential equations (DEs) modelling the time evolution of the state of the system as a trajectory through state space.

Non-linear differential equations are typically not analytically solvable. Hence, in earlier decades, out of necessity it was traditional to study linear dynamical systems, typically through the wave equation, diffusion equation, Poisson equation, Fourier transforms, and the like. Linearity has the great advantage of being additive, allowing solution techniques such as Green's functions. Weak non-linearity is handled through power series expansions in terms of small deviations from linearity.

Aside from quantum mechanics, however, the bulk of interesting systems in physics and beyond (from general relativity to chemical reaction kinetics and epidemics) are strongly non-linear:

> using a term like nonlinear science is, as the noted pioneer in experimental mathematics Stanislaw M. Ulam has observed, like referring to the bulk of zoology as the study of non-elephant animals [15].

This field of non-linear science has been developing, due to advances in the analysis of non-linear dynamical systems. In addition to advances in numerical solution, the field of non-linear dynamical systems encompasses the concepts of bifurcations (sudden changes in behaviour from a small change in the parameter value), chaos and sensitive dependence on initial conditions, classes of attractors (regions of state space where dissipative system trajectories end up) including strange attractors (where nearby trajectories eventually diverge, yet remain in the attractor), fractals, and more. See, for example, [16, 17].

Many of these systems are multi-dimensional, involving coupled differential equations, for example, Lotka-Volterra systems and chemical reaction networks. A multi-dimensional system can be represented as a network, where the nodes represent state variables, and the edges link to variables that affect the time evolution of the node. This leads to the concept of dynamics on networks.

In a spatial system, each point of space can be considered a state variable, affected by the neighbouring points. This leads to partial differential equations (PDEs), in contrast to ordinary differential equations (ODEs) that have derivatives with respect to a single variable, usually time. PDEs describe infinite dimensional systems with a spatial topology linking the state variables. Since space is continuous, PDEs include derivatives with respect to this continuous space, as well as with respect to time. The classic linear examples are Poisson's equation and the diffusion equation. A non-linear example is reaction-diffusion systems, such as those producing Turing patterns [18].

2.3 C: Computing

Computing is the science of information and processing. The subject includes a range of hierarchical structuring and software architectures, including layering software using virtual machines (VMs). One of the key abilities computational systems have that is crucial for life is the ability of *reflection* [19]: code can potentially refer to itself, run itself, and even modify itself.

Computing is often presented as a sub-branch of mathematics, a purely abstract discipline. However, all information, and all processing, have to be embodied somehow in the physical world, which places constraints on the possibilities. Computing can be viewed as a natural science [20].

The classical computation model, of the Turing Machine (or one of its equivalent formulations) is a symbolic, discrete time, discrete space, deterministic, 'ballistic' (dependent only on its initial condition; closed to inputs during execution), halting, sequential model. Other computational models exist, which break one or more of these assumptions, including stream processing and interactive computing [21] (which are open models that include communication with the environment during processing), analogue computing (where a physical model of the system under study is used as a computational analogue), general purpose analogue computing [22] (where mechanical or electrical circuits are used as physical analogues of an ODE model of the system), cellular automata (a form of parallel processing), Artificial Neural Networks (inspired by neural processing in the brain), and more.

These other computational models can be *simulated* by a classical digital computer—they are not uncomputable models [23]—but the point is about naturalness and explanatory power: the model should fit what it is modelling. Different models are suited to different requirements of information and processing, such as encoding and decoding information; control systems for sensing and interacting with an environment; cognitive approaches for memory and learning.

Since different models are appropriate for different problems, a complex problem such as life needs to include the composition of the relevant models, or some unification of them [24]. In particular, hybrid systems include a combination of both discrete and continuous models.

2.4 B-P: Bio-physical Systems

'Bio-physics' can simply mean using physics-based approaches to studying biological systems. While some such approaches may work, living systems are qualitatively different from the kinds of systems typically studied in physics, and so it is important to avoid 'physics envy' or 'physics chauvinism' in this cross-disciplinary topic.

Here I consider the topic to be the study of how the laws of physics constrain and enable life-like processes. It is the study of how physical embodiment affects life, recognising that not all features of life are purely due to genetics, but that some come from the physical properties of the material substrate itself [25].

This embodiment is most recognised at the substrate level, the level of molecular biology, biochemistry, chemical reactions and energetics, and the like [3]. Stiffness and supercoiling of DNA, protein folding, molecular diffusion in the cell, fluid dynamics of moving cells, and more, all these are physical properties. These properties result from highly evolved complex substrate molecules; such molecules can have very different properties from the non-evolved materials typically studied in physics. For example, entropy is usually conceptualised as a disorder. However, entropy increase can have non-intuitive outcomes for complex molecular systems, for example, of promoting segregation in certain cases:

> under strong confinement conditions, topologically distinct domains of a polymer complex effectively repel each other to maximize their conformational entropy, suggesting that duplicated circular chromosomes could partition spontaneously [26].

There are physical resources constraints at all levels, particularly those imposed by the environment, including sources of energy, materials, and niches.

2.5 C-B: Cyber-Bio Systems

'Computational biology' is the use of computers to analyse biological data and model biological systems and is not the topic of interest here. Rather, the topic is 'biological computation', the use of computational concepts as ways to explain and model biological processes, with the idea that some or many of these processes are intrinsically computational in nature.

When viewing living matter computationally, it can be approached in classical computing terms, from logic gates [27] to operating systems and beyond [3] (although there are differences between computer and cellular architectures [28]), or through using a broader concept of computing with models more suited to bio-substrates [29]. Computational analogues of biological processes may be suggestive; for example, partial evaluation [30] may be seen as a computational analogue of the Baldwin effect [31].

2.5.1 Information Processing

The clearest example of information and processing in biology is that of DNA and the genetic machinery that decodes and processes that information. This can be treated in an information-theoretic manner, including the role of error correction. The complexity of the information can be measured in terms of the mutual information between the genome and its environment; evolution increases this mutual information [32].

Different domains of life (bacteria, archea, and eukaryotes) have different 'operating systems', or cellular machinery, and so a gene or genome transplanted from one to another domain (or even within different clades of one domain) will not necessarily 'execute' in the same way [3]. The cellular machine reads the program (DNA), but can also under certain circumstances write/change it, allowing the program to change (as in self-modifying code).

2.5.2 Developmental Processes

Danchin [3, 33] views biological development as an algorithmic process, as iteration in space (parallelism) and time, constructing machinery that can replicate itself. He views this ability as one of the defining features of life: "the general principles for the construction of a self-replicating machine have nearly always overlooked the need for compartmentalization and metabolism" [33, p. 253].

Development as a form of algorithmic 'unfolding' includes complexity in the form of Bennett's logical depth [34]. Deep algorithms take time to unfold, and the processes of development (or evolution) can require that time.

Lindenmayer systems (L-systems) were developed initially to model growth processes in filaments [35, 36] and have been extended to model a host of plant-like developmental processes [37]. They are a form of generative grammar, where symbols in a string modelling the growing organism are rewritten in parallel to each generation, representing the parallel growth processes of each part of the organism. The field of Morphogenetic Engineering [38] explores the interplay of bottom-up self-organisation and top-down architecture to form programmable 'self-architecturing systems', typically in simulation, although the vision is of physical embodiment.

2.5.3 Synthetic Biology

Synthetic biology is the engineering side of genetic biology [39]. Viewing the genetic machinery as performing computations in a cell, with proteins as part of the signalling mechanism, it is natural to seek to engineer-in specific computations, for example, to manufacture particular proteins.

The computational model typically used in this case is based on genetic circuits modelled as discrete boolean circuits. However, DNA expression and control include processes outside this relatively simple model, such as methylation (extra-state information) and supercoiling (further regulation mechanisms) [40]. Additionally, real genetic machinery is 'leaky' (non-boolean) and stochastic. More sophisticated computational models are needed to better capture the relevant biological processes involved.

2.5.4 Bio-inspired Algorithms

Biological processes can themselves be taken as inspiration for a range of computational algorithms, such as metaheuristic optimisation. Evolutionary algorithms [41, 42], Particle Swarm Optimisation (PSO) [43, 44], Ant Colony Optimisation (ACO) [45], and a range of Artificial Immune algorithms [46] are used for search and optimisation; a range of artificial neural network [47, 48] algorithms and other biological network-inspired algorithms [49] are used for classification, prediction, and control.

Population-based optimisation algorithms can be classed as a form of *swarm intelligence* [50] where the desired outcome is a property of the 'fittest' individual in the population. In 'true' swarm intelligence algorithms, however, the result is due to the collective behaviour or configuration of the entire population (inspired by such biological behaviours as termites building a structure, or ants forming a bridge with their bodies); the swarm can be thought of as a single 'superorganism'.

Despite the range of inspirations used to develop such algorithms (some argue, much too wide a range [51]), there are few abstract underlying models. It might be argued that all the population-based optimisation algorithms are at heart the same [52]: they have a population of individuals, a fitness measure, a way of breeding new individuals based on this fitness, and a balance between exploration to find new solutions and exploitation of good solutions; they differ only in the details. Novelty search [53, 54], by eschewing exploitation for pure exploration, is arguably the most innovative advance in population-based algorithms in recent times. Similarly, the various network-based algorithms (neural, metabolic, signalling, and genetic regulatory) have a single conceptual model [55] and can be considered as population-based (nodes) with the addition of a relational structure (edges).

Such algorithms, although inspired by biology, are not particularly biologically plausible: they typically have much smaller populations, smaller 'genomes' (individual complexity), less sophisticated mechanisms for breeding new individuals, and less rich concepts of fitness than does biology itself. The presence of such a small set of abstract models, realised in such a broad range of bio-materials and mechanisms, demonstrates that much richness can be achieved using essentially the same mechanisms in a wide variety of contexts and scales.

2.6 C-P: Cyber-Physical Systems

'Cyber-physical' systems are typically embedded systems, where a conventional computer is embedded in and controls a physical system such as a robot or an 'intelligent' building. Here, however, I use the term in the context of a more life-like system, where the (unconventional) computational and information-processing aspects are embodied in a physical system: the processing 'brain' and the physical 'body' are intimately entwined, sensing, and interacting with an external environment in a feedback loop, as in cybernetic systems.

2.6.1 Embodiment

All computing, even classical computing, is embodied. Information is physical [56], embodied in material structure, from magnetic domains on a hard disk to sequences of bases in DNA. Processing is embodied in the physical dynamics of structured material, from flows of electrons in engineered circuits to oscillations of substrate properties in *in materio* reservoir computing [57, 58] and to feedback control of physical configurations in soft robotic bodies.

Classically, algorithms or programs are used to define and control the precise processing that occurs. Embodied processing may have no explicit program: it may be encoded in the values of certain material properties and configurations of the physical system. These may be engineered through some explicit learning process, as in reservoir computing, or evolved, as in natural organisms.

The focus of embodiment is often on embodied intelligence: how the brain and body work together [59] and influence each other [60]. However, it can cover close coupling between 'processing' and 'physical system' at all levels [61], not only high-level cognition. Although it is generally recognised that body morphology provides an important contribution to cognition and control, there is some dispute about whether there is any specifically computational contribution [62].

2.6.2 Information, Physics, and Life

Some authors identify information as a fundamental concept in physics [63]. Rather than subsume yet another concept under the domain of physics, however, here I consider computing to be a separate domain. The form information processing and computing take in an embodied context is typically not the same paradigm as in a conventional symbolic digital computer, but tends to involve more unconventional models and implementations of computing. In such cases, it is necessary to decide when a physical system is simply 'doing its thing', merely obeying the laws of physics, and when it is in addition also computing.

In order to determine when a particular physical process is performing computation, Horsman et al. [20, 64] use the definition: "the use of a physical system [the computer] to predict the outcome of an abstract evolution [the computation]." This use requires a representation relation between physical and abstract, which is used by a representational entity [65, 66]. One feature of this definition is that the representation relation is essentially arbitrary and can be realised in different ways independent of the physical substrate; see also Sect. 3.7.

The representational entity may be performing *intrinsic* computing internally (for example, by a bacterium to navigate towards food) or *extrinsic* computing by exploiting some external device (for example, a person using a PC). Thus, in addition to the argument that life requires computing (information and processing, Sect. 2.7), it can be argued that computing requires life, in order to *represent* information and processing, either embodied in itself, or by employing an artefact constructed to embody them.

2.6.3 Constraints and Limits

Computing is not merely a subset of mathematics, but it is not merely a subset of physics either [20]. However, given that computing is embodied in, and performed by, a physical system, it is clearly constrained by the laws of physics. This is just as true of classical computing, but tends to be neglected by theoretical computer science.

For example, there are physical limits on the computational speed of quantum gates, determined by fundamental physical dynamics [67]. Lloyd [68] has estimated the physical limits on the processing power of a one litre, one kilogram computer in terms of the values of fundamental physical constants. The Landauer principle [69] relates physics and information by linking to thermodynamics and irreversibility; Bennett [70] provides an excellent summary.

Even if a living system is not operating at the extremes of such fundamental constraints, there are still limits to consider because of its physical embodiment, including the source and amount of energy available to drive the dynamics; the source and quality of material to build and maintain the system; the ability to dispose of entropy in the form of waste heat and material.

2.7 Pulling It All Together: C-B-P

Living and life-like systems require consideration of (at least) the whole triangle of disciplines (Fig. 1):

- computing: information, processing, and 'intelligence';
- physics: material embodiment (of information and processing) in the structured matter, providing constraints and opportunities;
- biology: adaptation (evolution, learning), self-construction (growth, assembly), self-maintenance, open-endedness.

However, the computing, physics, and biology involved are not in their classical form. When we put together vertices to make the edges of the triangle, considering the overlap of pairs of disciplines, the science of each vertex is expanded and changed in the process. And these edges are interpreted differently in the consideration of life itself from the usual uses of the terms. Bringing all three together for a full science of the living requires further modifications and extensions.

2.7.1 Arbitrary Symbolic Relationships

Danchin [33] argues biology comprises *symbolic* relationships (for example, the genetic code) that, although constrained by physics, are nevertheless arbitrary (the genetic code could be different), so are not deducible from or reducible to physics. "Replaying the tape" of evolution [71] could well have resulted in a different genetic code or differences in other symbolic relationships in biology. "The objects that make biological functions happen often have no mechanical relationship with them; they are only their mediator, their *symbol*." [33] This symbolic nature has consequences for the underlying physics: it permits, constrains, and determines certain *classes* of symbols, but does not constrain the actual instances chosen. Even this constrained space is vast, and the realised actuality is just a small, arbitrary subset of this, chosen by evolution. We know that evolution is adept at finding and exploiting small differences and 'bugs' [72], so it might be that there is in fact some optimal symbol choice, but the richness of our biological world suggests there is a broad exploitable plateau around any such optimum or multiple optima.

Danchin [33] points out that this symbolic property allows "symbolic mediation" between quite different domains, such as representation within DNA and its realisation within proteins, and so the detailed nature of the underlying physical processes can be separated from the abstract symbolic processes. This separation is a form of emergence. Laughlin [73] points out that when emergent properties are insensitive to the substrate (as in this case), it is not possible to draw conclusions about the substrate from them. So we should not expect to be able to draw conclusions about the physical substrate from observing the symbolic biological processes.

2.7.2 Example Domains

Here I briefly discuss a few example domains that include the whole cyber-bio-physical spectrum to some degree: embodied cognition, swarm robotics, and morphogenetic architecture.

Embodied cognition. This area combines computationalism [74]—the brain as information processor—and cyber-physical embodiment—computational processes embodied in physical devices, or 'bodies'—interacting with an environment; the interaction provides a mechanism for symbol grounding. The focus is on cognition; the living body is a given. Cognition need not imply neural-style processing: Cohen [75] argues that the adaptive immune system is a cognitive system.

Swarm robotics. Swarm robotics combines the bio-inspired algorithms of swarm intelligence with embedded cyber-physical robotic systems [76]. The concept of using a multitude of small, simple, and (relatively) cheap robots, rather than engineering a single large, complicated, expensive device to do the same tasks, has led to the idea of "fast, cheap, and out of [top-down] control" systems [77, 78].

Swarm robotics research includes a range of biological concepts, such as morphogenesis (robot swarms self-organising into emergent shapes) [79], evolution [80], and open-endedness [81].

Current research tends to focus on the bio-inspired algorithms, and traditional embedded computational robot controllers. A more embodied computational control can be seen through research into soft robots and nanorobots.

Morphogenetic Architecture. The field of morphogenetic architecture [82] uses bio-inspired ideas of morphogenesis for designing buildings. A form of swarm robotics can be used to build structures, either directly, as ‘smart bricks’ that self-assemble, or indirectly, as ‘smart termites’ that assemble less smart materials [83]. While swarm robotics is based on biological analogues of animal populations, morphogenetic architecture is also based on plant behaviours [84]. Other aspects of ‘soft living architecture’ [85] include the homeostatic functioning of the completed building. Plants can also form the inspiration for novel sensors and actuators [86, 87] for use in ‘smart’ buildings.

2.7.3 Zoetics

Life is a cyber-bio-physical system, but that term does not trip readily off the tongue. The term ‘biology’ is already taken for the study of naturally occurring living systems, but, as I have discussed above, tends not to cover the entirety of information processing, embodied, life-like systems. The discipline of Artificial Life [4] includes these aspects, but might be thought to exclude natural life. The word ‘lyfe’ has been coined to describe any system that exhibits dissipation, autocatalysis, homeostasis, and learning [88], in the context of astrobiology; however, we want to include artificial systems.

The adjective ‘zoetic’ means[3] ‘of or relating to life: living, vital’ (from the Greek ζωή, *zōē*, life[4]), and so I use that to refer to all living systems, natural or artificial. In the next section, I overview some topics that are needed for Zoetic Science, then in Sect. 4 I discuss Zoetic Engineering.

3 Zoetic Science

Science, in a nutshell, is studying the world *as it is*, in order to build models of increasing explanatory and predictive power. Here I discuss some of the tools and topics (Fig. 2) that need extensions to deal with the particular properties of living systems; in Sect. 5, I briefly note some other topics not covered here.

3.1 Philosophy

The philosophical underpinnings of Zoetic Science need to be made clear: both how we perform scientific enquiry, and the basis of the underlying subject of study.

[3] https://www.merriam-webster.com/dictionary/zoetic.

[4] Not to be confused with the separate, though related, etymology of ‘zoology’ via Latin from the Greek ζῷον, *zōion*, animal.

Zoetic systems
complex, autopoietic,
dynamical, …

Tools
computer simulation ;
mathematics ;
philosophy ; …

Topics
metamaterials ; meta-dynamics
emergence ; embodiment ;
far-from-equilibrium thermodynamics ; …

Fig. 2 Some of the tools and topics needed within Zoetic science, discussed in Sect. 3

3.1.1 Epistemology

Not all science can be predictive the way physics aspires to be; the life sciences are simply too complex, too messy, and do not have the simplifying assumptions available to many branches of physics, such as well-separated length- and time-scales, identical particles, isolatable systems, pre-defined state spaces, and continuous dynamics. This leads to researchers in these disciplines having different relationships with abstractions, theories, models, experiments, data, and explanations [5, 89].

We need to ensure that Zoetic Science uses an appropriate method and philosophy for its mode of study, and not simply lift existing (often ill-defined, typically inappropriate) approaches from its component disciplines. This will require systematic reflection on the way the science is conducted: a second-order science [90].

3.1.2 Relational View

Leibniz proposed a relational model of space and time. Rather than Newton's absolute model where space and time exist independently, in Relationalism, "spatial and temporal relationships between objects and events are immediate and not reducible to space-time point relations, and all movement is the relational movement of bodies" [91].

A relational view can be applied to complex systems in general; modelled as a graph, the organisational structure (edges) takes priority over the material (nodes) [92]. Hence, we get the tale of the Ship of Theseus, asking if all the components are replaced, is it the 'same' ship? Yes, in a relational view, as the crucial structure has been preserved.

Relations can be first-class objects, allowing relations between relations [93]. Such a view helps explain why emergent properties are insensitive to the underlying material [73]: the emergence is building on the relational structure, not the specific matter that supports it. It also helps with the inclusion of information in a model: information is embodied in structure.

3.1.3 Process View

As Charlotte Perkins Gilman puts it: "Life is a verb, not a noun. Life is living, living is doing, life is that which is done by the organism." [94, Chap. X].

Ingold [95], arguing for an organism-centric biology, says:

> It must be a biology that asserts the primacy of processes over events, of relationships over entities, and of development over structure.

He also quotes Cassirer [96, p. 72], who says[5]

> Organic life exists only so far as it evolves in time. It is not a thing but a process—a never-resting continuous stream of events. In this stream nothing ever recurs in the same identical shape.

Life as a *process* is an essentially temporal, dynamical concept. Living systems embody many processes: they have a lifecycle of becoming, being, ceasing; they have sub-processes during this of maintaining, repairing, growing, adapting, learning, interacting, and more.

This suggests that a process view [97], rather than a substance view, is a more appropriate view of life [98–100]. However, life may be a verb, but it is not a *disembodied* verb. A pure process view may be too extreme: both process and matter are key [101]:

> neither of matter/object nor process/event is ontologically prior to the other; but rather, each is dependent on the other. [...] *(a) matter and objects by nature presuppose the participation in processes or events, and (b) processes and events by nature presuppose the existence of matter or objects.*

3.2 Systems

Rather than focussing on nouns (components) or verbs (processes), we can take a systems view, where the components and processes are packaged together in an integrated and structured (relational) whole.

3.2.1 Systems View

A systems view considers certain processes and material as a coherent whole [102]. A systems view is antithetical to a reductionist view in the following sense. A reductionist view starts by breaking the object of study into its components, in order to understand the components in isolation, then (hopefully) reassemble them to understand the system as a whole. The systems view, on the other hand, starts by examining the context of the system: what is its environment, what does it interact with, what is

[5] I give a slightly longer quotation here than appears in Ingold [95].

its history, and how does it behave in and because of its context? Since a key feature of living systems is their adaptability, examining their relationship with the context to which they adapt seems a reasonable point of view.

3.2.2 General Systems Theory

This idea of open systems, of wholes interacting with their environments, was the motivation for von Bertalanffy's development of General Systems Theory [103]. It grew out of thinking of biological organisms holistically. Such an approach is needed for non-linear systems where the parts are closely coupled (the very properties that make something a 'system', rather than an aggregation, a 'mere heap'). It is not just the components, but their relationships, their interactions, and dynamics, that make up a system and give rise to emergent system-level properties not seen in the individual components.

These early systems approaches tend to be produced from a physical rather than computational worldview. As such, they tend to focus more on relationships and patterns of structure, rather than the information and processes driving the dynamics. More modern approaches can take a more computational view.

3.2.3 Systems Biology

Systems Biology takes a system (that is, non-reductionist) view of biology, but the systems considered are mostly confined to the molecular/cellular level. Systems thinking [102] views systems such as these molecules and cells as themselves components and processes of larger systems, leading to a hierarchy of *systems of systems*. This hierarchy is not a pure tree [104]: peer-level systems are also coupled, although more weakly between systems than within systems. DeLanda [105] discusses structures comprising hierarchies and 'meshworks', and how these concepts can be applied across a range of scales and domains.

3.2.4 Autopoietic Systems

Autopoiesis [106] focuses on the organisation (the network of component-producing processes [107]) that makes a living system a 'unity'. For autopoietic ('self-producing') systems, their operation (the processes they perform) produces themselves (the components that embody those processes). Contrast this to an allopoietic ('other-producing') system, whose operation produces something other than what it is made of, and is produced by a system other than itself (for example, a factory machine, producing unrelated widgets, itself built elsewhere). Allopoetic systems are necessarily open since they need input to produce them, they are built; autopoeitic systems are to some degree closed since they build themselves (up to constraints of the second law of thermodynamics). Autopoetic organisation can be substrate-independent: "the same organization may be realized in different systems with different kinds of components as long as these components have the properties which realize the required relations" [106]. There is also work on realising autopoietic organisation in virtual systems [108].

3.2.5 Unnarratable Non-systems

Not all of life's processes are readily considered as systems. Consider the process of evolution. We have given it a name, 'thingified' it, but we do not view it as a system. It is a process within a living system of populations and ecosystems of organisms. Abbott [109] says that we understand the world through explanatory narratives of entities with agency. Parts of the world that do not have suitable structure are unnarratable and hence are not easily understood. He explores this example of evolution as one such process. It may be that complex systems are fundamentally unnarratable. "There isn't a story. It's more like tending a garden, only you're growing it with 10,000 other gardeners."[6] Gardening may be a good metaphor, or model, for thinking about interacting with complex multi-scale living systems [93, 111].

3.3 Mathematics

These complex, self-referential, process-oriented, autopoetic zoetic systems will need advanced mathematical underpinnings to define and model them.

3.3.1 Mathematical Self-reference

Autopoeisis (Sect. 3.2.4) is a circular process: A makes B makes C makes A. The mathematics of life needs to support circularity and self-reference. Such self-referential definitions (which include Russell's paradox [112]) are explicitly excluded in traditional mathematical set theory, through the axiom of foundation (essentially: every definition has to 'bottom out' eventually). It might be true that "the axiom of foundation has played almost no role in mathematics outside of set theory itself" [113], but the traditional set theory has an enormous impact on the way scientists model the world.

Self-referential definitions are perfectly allowable in non-wellfounded set (or hyperset) theory, which instead includes the axiom of anti-foundation, one form of which was developed to provide the semantics for Process Algebra formalisms in computer science [114]. This alternative form of set theory allows both endless chains of inclusion ("turtles all the way down") and the circular chains of inclusion needed for self-reference. Barwise and Etchemendy [113] provide a readable

[6] Abbott [109] attributes this quotation to Johnson [110]; I am unable to find it in that volume.

account of circularity; Hofstadter [115, 116] is the maestro of self-reference and 'strange loops'.

The more recent form of this approach is found in category-theoretic coalgebras with their corecursion; these are considered advanced mathematical topics.

3.3.2 Advanced Dynamical Systems Theories

Dynamical systems model many processes in physics (Sect. 2.2). In classical approaches, the behaviour of the system depends deterministically on the instantaneous internal state of the system. However, living and life-like systems have properties that do not satisfy these constraints. There are more advanced branches of dynamical systems theory that cover these aspects.

Openness. Life is an open system. Non-autonomous differential equations allow the modelling of environmental inputs through a time-dependent function (driven simple harmonic motion is a classic example).

Stochasticity. Living systems are variable, messy, and stochastic. Stochastic DEs allow modelling non-determinism in the form of noise. Not all variation in living systems is noise or error to be reduced: variation is the very driving force of evolution.

Memory and adaptation. Living systems have memory and adapt to experience and circumstance. Time-delay DEs and integro-differential equations allow modelling memory, or history of past events. Fractional order DEs allow modelling of long-term memory, phase transitions, and fractal structure and dynamics in complex systems [117].

Hybrid. Living systems tend to have components and processes that are best modelled by a combination of discrete (for the solid) and continuous (for the fluid) spatial components, and also a combination of discrete and continuous processes (both stepping and flowing, for example, a bouncing ball). This requires a close integration of two modelling approaches, for example, using hybrid dynamical systems. Further generalisation could include encompassing discrete-symbolic, probabilistic, and dynamical systems oriented views [24].

Growth. A growing system involves a change in the dimensionality of the modelled state space (Sect. 3.9): new dimensions mean new equations (for example, the production of new molecules in a chemical reaction network, or new species in a food web). This requires changing the model, which potentially requires self-reflection.

Jaeger [118] discusses what he dubs *wild systems* (such as the brain): high dimensional heterogeneous open systems driven by fast stochastic inputs, with non-stationary dynamical laws changing as a result of restructuring, evolution, and growth, and says that these "are wilder than today's dynamical systems theory can handle".

3.4 *Simulation and In Silico Models*

One approach to tackling such wild systems is to use computational, rather than purely mathematical, models and analyses.

3.4.1 Computational Simulation of Models

Simulating any system, evolved or engineered, needs to be done in a principled manner, based on the specific research questions or engineering goals, in order to develop a simulation that is fit-for-purpose [119]. Depending on the goals, simulations can be performed at different levels of abstraction, from high-level concepts and relationships to low-level details of specific functions. Irrespective of the level of abstraction, simulations can require considerable computational power, due to the complexity and scale of biological systems and engineered systems (for example, highly instrumented cities).

The specific models chosen to be the basis of the simulation need to match the relevant underlying structures of (the simulated aspects of) system under study. In addition to the physical and biological aspects needed, full models will also need to include the relevant computational and self-referential aspects. This may preclude certain classical approaches. For example, Danchin [3] notes that there is a "trend in systems biology, in which recursivity and information replace the usual concepts of differential equations, feedback and feedforward loops", and that "many of the models used in systems biology rely on hypotheses (continuous differential equations in particular) that are often too crude to offer a realistic representation of the cell."

3.4.2 Agent-Based Models (ABMs) and Simulation

ABM is in some sense the antithesis of dynamical systems modelling. Instead of modelling a global state space, and a system history as a trajectory through that space, ABM starts with individual conceptual agents, with potentially complex internal states and behaviours, that sense, move, and interact in some environment. Simulation then animates the model, allowing histories to be determined. This leads to a more experimental approach to model analysis.

ABMs can naturally incorporate growth, since spawning a new agent, as a result of some growth or reproductive behaviour, increases the number of dimensions in the model. Much work on computational morphogenesis (Sect. 2.5.2) uses ABMs. It is important to take note of biological processes when designing growth processes, and not simply use a default clocked approach. For example, there are synchronisation changes across different domains during biological development [120].

3.4.3 Computational Self-reference

As noted in Sects. 3.2.4, 3.3.1, and 3.7, living systems are self-referential. This self-reference is realised in the computational aspects of the systems. Computers can perform self-reference via reflection [19]: code can 'see itself', refer to itself, run itself, and modify itself. Indeed, modern computer architectures are designed to separate code and data, specifically to protect against (accidental) self-modification.

Classic ABMs are typically not self-referential at the code level. Typically, these are implemented in some form of object-oriented language, with fixed classes determining the possibilities. So the system is limited to a combinatoric assembly of pre-existing structures. Even if an agent can reflect on its own inner state, it does not typically modify its own code to produce new modes of sensing, locomotion, or reasoning, for example. It can be argued that self-referential ability is necessary for open-ended behaviours [9, 121]. Automata chemistries (where the agents are strings of assembly language code) are one suitable medium for building models that incorporate self-reference [122], and these can exhibit a form of semantic closure [123].

3.4.4 Computational Limitations

Landauer [124] notes a further consequence of the fact that computing is subject to physical limitations; these limit not just our computational capabilities, but also our theories: they constrain what we can calculate, and hence constrain the complexity of feasible theories. Landauer is concerned with physical laws, but this argument also applies to what we can calculate about (our models and theories of) living systems, which are large, messy, and complex, not readily amenable to simplifying assumptions. We may simply not be able to build and explore accurate and precise models of living systems at all the relevant scales: we may be restricted to only "a crude look at the whole" [125].

3.5 Scale, Complexity, and Emergence

Living systems and living technologies are large, complex, complicated,[7] and messy [127, Chap. 2]. They self-organise around their complexity through emergence and hierarchical structures. Such multi-scale complexity and emergence introduce their own challenges to understanding (see also Sect. 3.2.5).

Living systems have large numbers of certain components: trillions of cells making a human body; trillions more in the gut biome; billions of DNA bases; millions and

[7] The distinction between complexity and complication is not a sharp distinction, but may be thought of thus: Complexity is associated with dynamic, bottom-up self-organisation, as in complexity science, while complication is associated with top-down organisational structure, as often in engineering; systems with both features have been dubbed 'wicked' systems [126].

more in population sizes.[8] These huge numbers exhibit emergent properties: "more is different" [129]. For large numbers, macroscopic system approximations can often be made, although assumptions that all components of a certain type are 'identical' need to be treated with caution.

Contrariwise, other components, although crucial, are small in number. A cell has one instance of the DNA molecule, split into a few chromosomes, and small numbers of other macromolecules (while also having a huge number of smaller active molecules such as water). An organism has one or two instances of its major organs. For small numbers, microscopic system detailed investigations can often be made, although as open systems with context and feedback.

And then there are the intermediate scale mesoscopic system properties, where there are not enough particles for macroscopic averaging, but too many for feasible microscopic small number particle analysis. This domain can also be considered a length scale: intermediate between the atomic/molecular nanoscale and the everyday object macroscale, the mesoscale is where Brownian motion dominates [130].

Bains [131] describes the need to move "beyond the toy domain".[9] The very complexity and variation, in systems and their environments, the range of scales, are all key components and should not be simplified away until all that is left is a 'toy'.

There are many forms of emergence in the computational domain [132], but the one of most interest here is the idea of a Virtual Machine: an emulation of one computer (architecture) that runs on top of another (virtual or real) machine. A VM is a computational way of 'hiding' the computing substrate: for example, one cannot tell whether a given VM is running on a Windows, Apple, Linux, or other platforms, or indeed, on another VM.

VMs are not restricted to the digital computing realm; they are also advocated as a way of structuring cognitive processing and consciousness in the brain [133]. Even ignoring such cognitive levels, the Reservoir Computing model can be considered as a VM for *in materio* computing [57]: a single model that can run on a wide range of physical embodiments, including soft robotic bodies [134].

This idea meshes with a hierarchical view of the structure of living systems, thinking of each level of life (Sect. 2.1) as 'running' on, or an emergent process of, a physical machine provided by the lower level.

3.6 Far-From-Equilibrium Thermodynamics

Equilibrium thermodynamics is a fundamental core part of physics. However, living systems are far from equilibrium. As with the development of non-linear dynamical

[8] The minimum viable population of a species has been estimated at around 3500–5000 individuals [128], which should be contrasted with the tens or hundreds making up a typical evolutionary algorithm 'population'.

[9] Bains' argument is in the context of Origin of Life, but is also relevant to the study of life itself.

systems through three rough stages (linear, small perturbations, fully non-linear, Sect. 2.2.3), thermodynamics has a similar range:

Equilibrium systems. These are typically closed or isolated systems,[10] moving to equilibrium, a state of maximum entropy. They can use free energy to do work.

Non-equilibrium systems. Such systems can be analysed as small perturbations from equilibrium.

Far-from-equilibrium systems. These are open systems, maintained (or self-maintaining) in a far-from-equilibrium state by using a flux of free energy and/or material in, and entropy and waste material out. They are driven by dissipative systems that live on and exploit energy gradients.

In such systems, equilibrium concepts such as free energy, temperature, and entropy are no longer so well-defined. This means that equilibrium thermodynamics intuitions can be misleading when reasoning about living systems. For example, complex structure and information can accumulate by exploiting noise through the use of ratchet mechanisms [135, 136].

3.7 Embodiment v. Virtual Physics

Everything is physical. Information, computing, and biological processes are embodied in structured physical material. Physicality provides the substance and constraints.

This leads to the question: can 'virtual life' exist? The Artificial Life community does much work *in silico*: is this a mere simulation, or can it ever be really alive? Can artificial chemistries [137, 138] and artificial physics support artificial (but still real) life? There is evidence that artificial resource limits can be exploited by simulated systems; for example, more diversity can occur in artificially evolving systems with 'mass' conservation [49, 139] and 'energy' constraints [140]. In a virtual system, there is a need to minimise the hard-wired 'physics', and allow as much of the simulated system as possible to evolve, to be 'soft' [141].

Can there be 'virtual embodiment'? It may be that embodiment is a property "of any suitably complex system engaged in a complex intertwined feedback relationship with its suitably complex environment" [61].

Rosen [142] disagrees. He builds a model where "life is closed to efficient cause", where every aspect is entailed by another aspect; in particular, he considers metabolism f, repair of metabolism Φ, and repair of metabolism b. Kercel [143], who provides an informative summary of Rosen's position, summarises this as $\Phi \vdash f \vdash b \vdash \Phi$. This is an inherently circular, self-referential definition (Sect. 3.4.3), similar to that of autopoiesis (Sect. 3.2.4).

Rosen argues that his model entails a need for physics to provide the situation that *grounds*, or gives meaning to, the ambiguous circularity and that this meaning can-

[10] In a closed system, matter cannot move in or out, but energy can, for example, in a closed system in a constant temperature heat bath. In an isolated system, energy is likewise banned from moving in or out and is hence conserved.

not be provided in a simulation with its ungrounded virtual physics. He also argues that it demonstrates the inadequacy of mere mechanistic models, which do not have this closed loop of causation, this property of self-definition. However, a simulation running on a universal computer is not a 'mere' machine (Sect. 3.9): universal computation supports self-reference and circularity, unlike mechanical devices. Hence, a virtual physics in a simulation sufficient to support self-reference, strange loops, and self-modifying code may we be sufficient to support (virtual) life.

Danchin [33] argues (Sect. 2.7.1) that the key to life is the symbolic relationships. These could be based on other physico-chemical substrates [144]; could they even include virtual *in silico* substrates, contrary to Rosen here? It seems plausible: life evolves the abstract symbolic control layer, a virtual machine; the ambiguity inherent in self-reference is resolved not by physical grounding, but by the particular, if arbitrary, symbolic representation chosen. Indeed, the demonstration of this arbitrariness can be used to distinguish intrinsic computing from non-computational processes in organisms [65]. It is not just symbols that can be implemented in a variety of ways: whole conceptual models can. As mentioned in Sect. 2.5.4, populations and networks are abstract models realised in a host of different manners. Danchin argues the symbols gain meaning only in context: "A cell can be defined as a machine that puts the genetic program into operation *according to the data provided by its environment*" [33, p. 270]. That meaning and context could be provided by a virtual environment.

However, Rosen's arguments are subtle and difficult and deserve further attention: if he is wrong, just where and why is he wrong? But if he is right, so much the worse for virtual ALife.

3.8 Metamaterials

Living systems are embodied in structured physical material. The structure is crucial to the material's ability to support complex information storage and processes. In biology, these materials are typically complex information-bearing polymers (DNA, RNA, and proteins).

Metamaterials are materials that have been highly engineered to have functional properties not present in ordinary materials. These can be electrical, optical, mechanical, or other properties. These properties can be programmable [145].

Metamaterials can be engineered to have computational properties. Classical computing takes place in what can be considered as computational metamaterials: silicon chips. Other metamaterials can be engineered to support other forms of classical computing, for example, mechanically realised boolean logic [146]. However, classical computing is at odds with the more 'natural' functions of materials [147]. Metamaterials can also be engineered to have unconventional computing properties [148], for example, as the substrate for *in materio* reservoir computing [58] and more general neuromorphic computing [149], for optical analogue computing [150], and as fluidic patterned controllers for soft robotics [151].

With suitable engineering, metamaterials can have simultaneous computational and physical functional properties: 'smart functional matter'. For example, oscillating MEMS (micro-electromechanical system) beams can be used as accelerometers and can also be used as reservoir computers [152]; combining these functionalities gives a device that can sense acceleration and process its sensing via reservoir computing in the same metamaterial [153]. Soft condensed matter might provide a stepping stone to more biological metamaterials [154].

We can then think of natural living substrates as highly *evolved* metamaterials, with both functional and computational properties. Indeed, DNA can be used as an engineered evolved metamaterial for DNA tiling [155] and DNA origami [156, 157]: its evolved information-bearing properties are engineered into self-assembling molecular-scale physical structures. In order to discover appropriate metamaterials for unconventional forms of living computation, it may be necessary to co-design the computational model and its supporting metamaterial [158].

So artificial living systems will be embodied in highly engineered computational and functional metamaterials. Virtual life, if it is possible (Sect. 3.7), will need appropriate virtual metamaterials for its embodiment.

3.9 Meta-Dynamics

The *machine metaphor*, that living systems are, or can be considered to be, *machines*, is a prevalent one. Some argue about the cultural meaning of the metaphor itself [159]. Others argue against its use in biology, for example, Woese [160] says:

> Let's stop looking at the organism purely as a molecular machine. The machine metaphor certainly provides insights, but these come at the price of overlooking much of what biology is. Machines are not made of parts that continually turn over, renew. The organism is. Machines are stable and accurate because they are designed and built to be so. The stability of an organism lies in resilience, the homeostatic capacity to reestablish itself.

I suggest that, rather than drawing a categorical distinction between machines and organisms, thereby running the risk of imputing the latter with some sort of *élan vital*, we should consider a spectrum, with 'mere' machines at one end, and living machines at the other.

Rao [161, p. 144] links the difference between 'mere' machine and organic processes as the nature of the changes they undergo:

> Where change in the machine metaphor is a process of stepwise re-engineering, in the other, more organic metaphors, change is a process of generative growth, ontogeny and self-organization.

So the spectrum of interest captures the forms of a structural change the system undergoes: it is along the dimension of the system's meta-dynamics (the dynamics of dynamics).

To reiterate, a dynamical system (Sect. 2.2.3) has a *state variable* (a value, typically a scalar or vector quantity) and a *state space* encompassing all possible values the state variable can take; a system's *dynamics* is a trajectory through the state space: the sequence of values its state variable takes through time. For meta-dynamics, the variable is itself a state space, and the (meta)state space is the set of all these values (all these state spaces); a (meta)trajectory moves through this meta-state space: the sequence of state spaces passed through with time. If the meta-dynamics is on a much longer timescale than the underlying dynamics, the two processes can be considered separately to some degree.

Physics uses dynamical systems as a modelling approach (Sect. 2.2.3), typically assuming a pre-defined, fixed dimensional state space. Computation can be viewed in terms of dynamical systems too [162], and the state space itself changes as variables go in and out of scope. These changes are not typically thought of in (meta)dynamical systems terms; work that does consider this aspect to some degree includes $(DS)^2$, 'dynamical systems with a dynamical structure' [163, 164], discrete dynamical systems automata [165], and the dynamics of networks (where the nodes represent variables, so new nodes represent new variables in a changing state space) such as in chemical organisation theory (COT):

> Complex dynamical reaction networks consisting of many components that interact and produce each other are difficult to understand, especially, when new component types may appear and present component types may vanish completely [166].

Living, growing systems naturally have a state space of increasing dimension and naturally have a meta-dynamics.

The spectrum from mere machine to living system can then be characterised by the trajectories of its meta-dynamics:

Mere machines, mechanisms, have a dynamics (behaviour/motion), but a very limited and mostly extrinsic meta-dynamics. They do wear and break, but any maintenance, repairs, upgrades, remodelling, debugging, etc. are extrinsic changes, happening discretely. Their functions, their trajectories, are typically cyclic, involving resetting to a given earlier state in the fixed state space, for example, thermodynamic work cycles and factory machines producing widget after widget. They have essentially no meta-dynamics.

Computational machines, computers, are more complex. Due to computational incompleteness and uncomputability, their dynamics can be unpredictable, only discoverable through executing the relevant program. Even if individual algorithms are closed during execution, overall a computer is an open dynamical system [167], taking user inputs, and providing a stream of outputs, throughout its operation. This open operation of a computer does not typically involve a reset to an earlier state: it takes input, stores data, learns, adapts, and is upgraded, all of which are a form of both intrinsic and extrinsic meta-dynamics, as its state space changes. But in principle computers can return (or rather, be returned) to earlier check pointed states; their trajectories can contain occasional cycles: rolling back a transaction, switched off and on again, factory reset. They have weak meta-dynamics.

Living machines, organisms, are characterised by a complex and rich intrinsic meta-dynamics: they continuously self-maintain, develop, grow, mature, behave, learn, etc.

Much of this meta-dynamics is intrinsic (although to a degree also extrinsic, due to interaction with a complex of other organisms and a physical environment). Living systems typically cannot be reset to an earlier state: the change is irreversible, and the trajectories are not cyclic. They have highly non-trivial intrinsic meta-dynamics.

4 Zoetic Engineering

So to progress Zoetic Science, the science of living systems, evolved, engineered, or possibly virtual, requires specific advancements in dynamical and meta-dynamical open systems, simulation, far-from-equilibrium thermodynamics, and metamaterials to cope with self-reference and self-production, multi-scale modelling, embodied computing, and growth. There will be more areas needing advancement, too. How to make progress with all these seemingly disparate branches of science? And how to ensure that the advances in the sub-disciplines are the right ones for the overall domain, and do not simply wander off into areas that are tractable but irrelevant?

We can take a lesson from the development of classical thermodynamics. Today it is core physics, a scientific discipline. However, historically during the Industrial Revolution, it was developed in response to an *engineering* need: to understand the fundamental limits to the efficiency of steam engines.

Engineering, in a nutshell, is making the world *as we want it to be*,[11] by building artefacts of increasing sophistication and capability. We could develop a new discipline specifically of Zoetic Engineering, developing living technologies of increasing sophistication, and use that to kick-start a grounded discipline of Zoetic Science. This would ideally result in a tight feedback loop of increasingly sophisticated artefacts, requiring and grounding increasingly sophisticated scientific advances, enabling further progress in the engineering domain, and so on.

Today, the technology that *constructs* an artefact is separate from the technology *of* the artefact, even biomimetic artefacts. Tomorrow, the technology is *both* the artefact *and* its construction and maintenance, all in one: a 'living' technology. With the domain focus on self-production through mesoscale self-organisation, self-assembly, and growth, an initial application of Zoetic Engineering might be a novel manufacturing process: self-producing artefacts.

Two of the example domains noted above (Sect. 2.7.2), swarm robotics and morphogenetic architecture, might provide fruitful starting points. The living technology would be an open system, responsive to and adapting to inputs during its lifetime. For architecture, the gardening metaphor is appropriate, providing inputs to guide and shape growth; for swarms, a shepherding metaphor might also find use. The artefact does not have to be entirely living, it can benefit from a hybrid approach. Growth could exploit classical building (such as scaffolding or trellis for support, and inorganic pipes and wires). It could also exploit a complementary living con-

[11] One might argue that most engineering projects fail in this regard, due to our inability, or lack of desire, to anticipate and mitigate for all the related unwanted consequences.

struction technology based on assemblers of termite-like swarms; swarms can also interact with the physical environment in a complex manner [168]. Then 'gardening' (planting, training, pruning [169], landscaping) and 'shepherding' tailor the growth context [84, 111].

5 Conclusions

Living systems are machines, but are not 'mere' machines. They are highly evolved or engineered, self-referential, computational, adaptive, stochastic, far-from-equilibrium machines, embodied in smart functional metamaterials, with non-trivial meta-dynamics: *meta-machines*,[12] if you like.

Understanding and engineering such zoetic systems require a new synthesis of biology, computing, and physics, where all three disciplines are extended and moved out of their classical comfort zones. This overview has omitted any detailed discussion of several other linked disciplines which are also part of the overall synthesis, including abiogenesis, the origins of life [172]; biochemistry (all the non-DNA/protein but nonetheless complex biochemicals in cells), chemistry (including the self-assembly of complexity through constrained combinatorics) and chemical engineering; computationalism (the view that the brain is an information-processing organ, a computer, implying that a computer could be a brain, could think) [74]; cybernetics and control systems, including second-order (recursive, self-referential) cybernetics; the ethics of living artefacts; healthy flourishing systems *v.* diseased systems, including ecological concepts from symbiosis and parasitism; neuromorphic computing; probability and statistics; and more.

Zoetic Science could be grounded by Zoetic Engineering: the production of living, or life-like, technologies and artefacts. Where might this lead? I am reminded of the statement by James Burke in his TV series *Connections*, on the long complex history of new ideas and new technologies, that themselves lead to further ideas and technologies:

> we live in a situation we inherited, as a result of a long and complex series of events through history. At no time in the past could anybody have known that what they were doing then would end up like this now [173].

[12] The prefix 'meta' originally meant simply 'after', but came to the additional meaning of 'above' or 'transcending', and now also includes the meaning of 'change' or 'transformation', and more recently of 'self-reference' (as in meta-X is the X of X). The 'transcending' meaning comes from a misunderstanding of the derivation of the word 'metaphysics': the term as originally coined did not mean 'transcending physics', but rather as 'Aristotle's book after the one called Physics'.

'Metamaterials' are *changed* materials: changed by engineering in this case. 'Meta-dynamics' is the *self-referential* use: the dynamics of dynamics. Given the prevalence of the prefix in the topics of interest here, it would be nice to be able to bundle the concepts into the term 'metaphysics', but it has already been taken for that unrelated Aristotelian topic. (To add further confusion to naming, 'meta-dynamics' is also the name of a computational simulation technique [170, 171], although the original 2002 paper does not name it thus.)

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