Towards a More Rigorous Foundation of Complex Adaptive Systems in Management Science: Dealing with Misnomers and Metaphors

Leslie Klieb[1, 2] , Merle Rhoades[1, 3], Bill McKelvey [4]
[1] University of Liverpool in partnership with Laureate Education, Inc., Liverpool, UK
[2] Webster University Thailand, Bangkok, Thailand
[3] East Colorado SBDC and U. of Northern Colorado, Greeley, CO, USA
[4] Kedge Business School, Marseille, France
{leslieklieb@gmail.com, bbr@q.com, mckelveybill1@gmail.com}

Abstract—**This paper provides a framework for organizational Complex Adaptive Systems without directly referring to biology (evolution theory), physics and mathematics. The model can reproduce most of standard management science and sheds light on new ideas in corporate strategy. Possibilities for numerical simulation are discussed.**

Keywords-adaptive systems; management science; agents; modelling.

I. INTRODUCTION

The existing literature about organizations seen through a Complex Adaptive Systems (CAS) lens (Lewin, 1992 [1]; Kauffman, 1993 [2]; Holland, 1995 [3]; Maguire et al., 2006 [4]) usually borrows for a discussion of system properties from biology, mainly from evolutionary dynamics (Holland, 1975 [5]; Mandelbrot, 1982 [6]; Nicolis and Prigogine, 1989 [7]; Kauffman, 1993 [2]; Aldrich, 1999 [8]; McKelvey, 1982 [9]; Nelson and Winter, 1982 [10]) and from physics (Prigogine, 1955 [11]; Kaye, 1993 [12]; Cramer, 1993 [13]; Gell-Mann, 1994 [14]). Not only does this make this the literature extremely hard to read for managerial scientists and practitioners, it also obscures that CAS in social science have essential differences with biological systems. We show here that organizational systems (businesses, but not exclusively) can be easily interpreted as a collection of agents (Carley, 1992 [15], 1999 [16]; Carley and Hill, 2001 [17]). While standard CAS literature avoids specifying the attributes of the agents and their interactions (schemata), we show here that specifying these schemata leads to an easily understandable framework that encompasses most of standard business science, and gives a clear interpretation of most standard CAS literature on organizations. It also makes it easier to see what the differences are relative to the evolution of biological systems (McKelvey, 1982 [9]; 1994[18]; Maguire et al, 2006 [4]; McKelvey et al., 2013 [19]).

The plan of this work is as follows. In Section II, a brief overview of some salient literature is given. In section III, schemata between agents are formulated. After that, the rest of the paper is devoted to how these schemata, although admittedly (too) simple to be predictive of all behavior of agents, are sufficient to reproduce most standard CAS management literature. So, in Section IV, sudden shifts in phase space from punctuated equilibrium are discussed. Section V focuses on the Edge of Chaos. Section VI focuses on how the agent description reduces to many standard management science descriptions when certain interactions are small compared with others and therefore can be neglected. As these standard management descriptions have been usually experimentally verified, this provides the necessary link with empirical descriptions in a large number of limiting cases. Section VII provides an interpretation of the Soft System Methodology in an agent view. Section VIII does the same for Action Research. Section IX provides some conclusions and an outlook.

II. LITERATURE REVIEW FOR CAS

Especially when the application of CAS to business was developed, authors frequently considered the business ecology as analogous to evolutionary biological systems (for instance Kauffman, 1993 [2]; Bak, 1996 [20]; Anderson, 1999 [21], Gell-Mann, 1994 [14]). This has often been very fruitful. McKelvey (1982, 1994) [9][18], McKelvey et al. (2013) [19], and in an unpublished work McKelvey (2002) [22] identified many patterns that are common between the dynamics of biological systems under influence of evolutionary forces and the dynamics of business systems. However, the relationship between biological and social CAS remains unclear. In this work, we show:

- Both may be represented and studied via agent-based (computational) models of system dynamics (aggregates of agents)
- In general, models need to be sufficiently detailed so that they can reproduce the characteristics of dynamics. On the other hand, models should focus on essentials and not be cluttered with too many details. Davis and Eisenhardt (2007) [23] called this the “sweet spot” of model design. We give arguments here that it is possible to develop successful models of both biological and business dynamics independently. Such independent modeling has already been done successfully for biology, and it will be done in a heuristic way in this work for the kinds of CAS systems in human organizations. Such a model for social organizations

 ISBN: 978-1-61208-341-4

can reproduce most of business science, and is, therefore, empirically valid. A useful beginning is the model developed by Carley and Hill (2001) [17].

- There is a large similarity between the two models, and this explains similarities in evolutionary dynamics, like the patterns found by McKelvey (2002) [22].

- There are also essential differences between the two models, and this explains where the analogies break down. Biology is a metaphor, not an explanation for business science (McKelvey et al., 2013 [19]).

III. THE MODEL

As postulated by an agent-model of CAS that applies to most of management science, agents have the following attributes—mostly developed early on by Carley et al. (e.g., Carley, 1992 [15], 1999 [16], 2002 [24]; Carley and Svoboda, 1996 [25]; Carley and Hill, 2001[17]):

- Needs for food, energy, shelter, and similar (equivalent needs for organizations)
- Need company and bonding mediated by connections (attractive force)
- Need space (privacy, physical room (repellent force)
- Needs are hierarchical, a lower more essential need can overcome a higher need, analogous to Maslow's hierarchy.
- Intentionality (considered also as a need, for the ease of discussion here)
- Agents can (and actually like) to learn (learning = behavior change under influence of stimuli on longer time scales).
- Agents cannot have perfect knowledge about other agents. There is always interpretation.

Satisfying needs comes with costs. The number of needs is countable, possibly (and probably) infinite. Agents in this context can be people but also organizations, and every other kind of system that is studied in social science. We will show that the above needs are sufficient to define a CAS. The system shows many characteristics of CAS as discussed in the management literature and provides helpful guidance for managers in understanding system effects.

Agents try to do what they perceive as best for them to fulfil their needs and survive while taking into account the costs to do so, and therefore, make an assessment of their needs and situation and try to improve their situation. CAS literature calls this measure of how well needs are satisfied (fitness), but it is a perception of 'fitness' (if fitness is taken as defined in biology by ability for survival). Perceived fitness is an assessment how well various needs are satisfied and in which direction an agent would like to move in order to satisfy better the needs and enhance survival or other measures of success. This includes an outlook for the future. Perceived utility is the gain that can be made in perceived fitness (a small extension of or maybe identification with the economic term). Utility is a function of the needs.

A technical assumption is based on transitivity of choices: If Choice A is preferred over B and also B is preferred over C, then A is preferred over C. In this case, perceived fitness can be measured on a one-dimensional scale, it is a mathematical non-linear function of all variables/needs.

Given these assumptions, agents always have a perception of a best course of action. This is sufficient to define a fitness landscape and a phase space consisting of {needs x perceived fitness}. The dynamics of agents are determined by their attempts to increase perceived fitness. Their interactions lead to a CAS: the dynamics are irreducible (cannot be compartmentalized). Agents form systems because of the long-range attraction and short-range repulsion, which leads to an optimal size with respect to costs. An example provides the work by Bettencourt, 2013 [26] on the size of cities or the work of Krugman, 1996 [27] on spatial economy. The schemata also cause the system to operate far from equilibrium (Lewin, 1992 [1]; Cramer, 1993 [13]). The above needs/schemata are insufficient to explain all observed dynamics. For instance, for human agents, psychological factors (in principle, part of the schemata) are not included in the above model. In modern times, dynamics between agents are mostly determined by other agents and not by a non-human environment (like forces of nature). The interaction between agents is now termed co-evolution (Kauffman, 1993 [2]).

In a business science context, agents are heterogeneous; they can be and usually are different. These differences are expressed in that they react differently to their environment and to other agents (because of differences in attributes), and that therefore they tend to have different interactions. Technically, agents have different schemata (Carley, 1992 [15], 1999 [15]; Carley and Hill, 2001 [17]; Ilgen and Hulin, 2000 [28]).

IV. PUNCTUATED EQUILIBRIUM

Most agents are close to a local peak, but not to a more optimal but (usually) more distant global peak (Carley and Svoboda, 1996 [25]). Usually, most changes in an agent's environment can be accommodated by making gradual moves. Changes in environment can be limited to changes in the relative height of peaks. Sometimes peaks disappear or new peaks emerge. Such events can have a dramatic influence, because disappearance or growth of one peak can lead to a domino effect and influence peaks in the neighborhood of those peaks that in turn influence peaks in their neighborhood and so on, leading to a major configuration (Barabási, 2005 [29]). This can lead to a huge change in the fitness landscape for an agent. This shows that often changes for an agent can be accommodated slowly, close to a dynamic equilibrium, but sometimes the fitness landscape, and with that the dynamics of an agent, changes tremendously and no slow (adiabatic) change is possible anymore. Equilibrium is punctuated by sudden disruptions (Bak and Sneppen, 1993 [30]; Romanelli and Tushman,

 ISBN: 978-1-61208-341-4

1994 [31]; Bak, 1996 [20]; Gould and Eldredge, 2000 [32]). Disruptive technology is an example of this (Andriani and Cohen, 2013 [33]).

V. THE EDGE OF CHAOS

In every assembly of such agents, intuitively, there are three regions: not enough meaningful interaction between them to speak of a system, enough interaction so that tacit and explicit knowledge is exchanged between nodes, and a region in which too many interactions make the system uncontrollable and overreacting (Langton, 1990 [34]; Kauffman and Johnson, 1991 [35]; Lewin, 1992 [1]; Brown and Eisenhardt, 1998 [36]; Pascale, Millemann, and Gioja, 1999 [37]). The transition between "enough interaction" and "too much" is metaphorically called the edge of chaos. Although in certain mathematical models in biology the uncontrollable region is chaotic in the mathematical sense, here the dynamics is not predictable enough to make such general mathematical statements as the existence and size of Lyapunov coefficients (Montroll and Badger, 1974 [38]).

In organizations, overly connected regions of the CAS that have too few links with their environment are called silos (LaBonte, 2001 [39]; Diamond, Stein, and Allcorn, 2002 [40]; Dell, 2005 [41]). They are a sad consequence of the heterogeneity of agents, which in good cases makes the system more adaptive. If agents were homogeneous, exactly similar, each agent would have the same type of interactions with other agents, and the phase diagram would still have symmetry breaking, but not on such a large scale. It would be homogenous throughout each of the three regions. Therefore, in an organization the three-region model is simplistic. Regions of more and less connections are scattered all over the organization (often department-wise, or otherwise as informal groups, see above for arguments how such more or less stable subsystems diminish costs). It does not help that because of fractality (i.e., self-similarity), these subsystems have their own edge of chaos (Schroeder, 1991 [42]). A silo is an uncontrollable region where link inside link density is too high from the point of view of controllability by the enveloping organization. Intuitively, it is similar to a type of attractor (fixed point, limit cycle, limit torus, strange attractor, not necessarily chaotic).

VI. LINKS WITH KNOWN MANAGEMENT SCIENCE

The agent model given here reproduces a large number of disparate management fields of study. It reproduces most of the standard CAS literature. It deviates where the assumptions are different, for instance Stacey's (2011) [43] theory of responsive processes stresses very different interactions between agents (different schemata). This makes the scope of applicability of Stacey's theories very different. In fact, there is increasing evidence that various kinds of both static and dynamic aspects of organizations are self-similar from small to large to environmental scales, Batty and Longley (2004) [44], Newman (2005) [45], Andriani and McKelvey, (2007 [46], 2009 [47]), McKelvey and Salmador (2011) [48], and McKelvey, Lichtenstein and Andriani (2013) [49] offer 200+ examples of how the many variables characterizing organizations result in fractal (i.e., Pareto long tailed rather than normal) distributions.

A. The agent in its environment and misalignment issues: static descriptions

Organizational CASs are fractal systems, they exhibit self-similarity in their dynamics, and because of this, similar social structures arise at various sizes (Stanley et al., 1996 [50]; Solé, 2001 [51]; Andriani and McKelvey, 2007 [46], 2009 [47]). Agents are part of many groups of different sizes. All these groups have their own perception of fitness. These perceptions are in general not aligned. The result is that an agent in a group may feel misalignment up to a certain degree, between its own perception and the perceptions of fitness (mission, goal, purpose) of the group to which it belongs. Examples:

Resistance to change: An agent's perception of its own fitness clashes with the perception of the fitness of a group it belongs to. This is usually its employer or boss, but can be a religious or political or other organization.

Principal Agent Problem: Aided by asymmetric information, perception of fitness of a C-level director is misaligned with the perception of fitness of the owners of the firm (who are after maximization of shareholder profit). Note: The existence of asymmetric information comes from the postulate in the schemata that no objective knowledge is possible.

Turnover: an agent feels so much misalignment that it is leaving its group (examples are in employment, marriage, club membership, etc.)

Cognitive dissonance: An agent tries to reconcile misalignment between its own perception of fitness with the group's perception of fitness (Festinger, 1947 [53]). Values held by agents can be understood as the agent's ideas about best direction to go, so these values are part of utility in this scheme.

Ajzen's (2011) theory of planned behavior [52] recognizes environment, i.e., the interactions that one agent feels from other ones, via the subjective norm and shows that this influences the dynamics (intentions leading to behaviors).

Marketing: People do not always go for the least expensive purchase, because buying upscale signals to others their ability to survive (analogous to the potlatch). Giving of presents serves the same purpose.

Global Controller: Holland, 1988 [54] notes that in biological CASs there is no global controller, i.e., no paid boss – even the queen bee doesn't get paid to tell worker bees what to do. However, all organizations have a CEO who is paid to take charge, take control, etc., and lower-level managers who are also paid to be in charge. This asymmetry between agents is probably the most fundamental difference between biological species and herds vs. human organizations.

Theories of leadership: Complex Leadership Theory (CLT). Continuing where Holland (1988) [54] left off, Uhl-Bien et al. (2007) [55] point to the unavoidable consequences of fractality and heterogeneity. In every group, (subsystem), leaders and followers will emerge, because agents are heterogeneous and interactions are asymmetric. Some groups are labelled "formal" and others "informal" but that is pure convention. Leaders in formal group are called administrative leaders and function differently towards the environment and are usually recognized by it. Leadership in informal groups ("adaptive leadership") is often not recognized outside the group. In this framework, it becomes very hard to evaluate objectively people's contributions. Leaders of one group can enhance their fitness and the fitness of their own group sometimes by co-opting the leaders that spontaneously emerged from a different group. This process is called enabling leadership.

Leadership Exchange Theory: All leadership occurs in the space between agents. Theories like Leadership Exchange Theory amount to a more precise specification of the schemata.

Resource-based view of the firm applies to all groups (systems). There is always an advantage in pooling resources from the postulate of bonding.

Test particle approach: Introduce one agent into an organization – i.e., an agent is hired. In a first approximation, the agent's dynamics starts to be determined by the interaction of its own perception of fitness and the influence of all the other agents. This influence of all the other agents on a single agent is called organizational culture. In a second approximation, one can "calculate" the influence that this particular agent's new dynamics (which includes its own previous learning, experience and other attributes) is having on the organization. Then one can "calculate" again the influence of the new organizational dynamics on the person, and so finally arrive at a self-consistent description (in theory, not in practice). The second approximation, the influence of the agent on the culture of its group, is alternatively called leadership, art, volunteerism, and any other way agent influences on a system to which it belongs are named.

All the above aspects have in common that they mirror standard areas of business science. However, in the conventional treatment these normally disparate areas are not put into one unified framework. This shows that the schemata used in this description are powerful enough (Cramer, 1993 [13]) to reproduce standard theory (or alternatively, if you want that interpretation, that many management theories have very simple assumptions about the interactions of the agents) (Williamson, 1975 [56]; Read, 1990 [57]). However, in the above applications they do not really test the dynamics of the system.

B. The agent in its environment: dynamic descriptions

Dynamic capabilities: Many benefits of groups result from pooled resources. This is the resource-based view of the firm (Barney, 1991 [58]; Barney, Wright, and Ketchen, 2001 [59]) (which applies in this view to every CAS, as there is no fundamental difference between a firm and any other CAS). So, this theory is really the resource-based view of the group or system, and results from the nature of the fundamental interactions between agents. When it is necessary for the CAS to increase its fitness because of external events (threats, opportunities), often its resources need to be re-configured. This will need to be done in different ways depending on the amount of turbulence and change. Eisenhardt and Martin, 2000 [60], discern high-velocity and medium-low velocity markets. Under high turbulence, many tools, like standard strategic forecasts, lose their value.

Strategy: Depends on the ability to make a moderately successful prediction of the future of the group where one belongs. Events that can be classified as "punctuated equilibrium" or "black swans" (Taleb, 2007 [61]) are inherently nearly impossible to predict accurately ("black swans" result from the fat tails of power laws; the descriptions of the domino theory of punctuated equilibrium and power laws are probably related). Under moderate turbulence, some prediction might be possible (Eisenhardt and Martin, 19[60]. In the transition from low turbulence to high turbulence regions, a prediction about future changes in the fitness landscape, and therefore strategy, becomes more and more unreliable (Holland, 1995 [3]; Krugman, 1996 [27]; Dooley and Van de Ven, 1999 [62]; Sornette, 2003 [63]; De Vany, 2004 [64]; Sornette et al., 2004 [65]; Baum and McKelvey, 2006 [66]). One of the CAS alternatives is to strengthen connections and upgrade the knowledge of the agents (change their schemata by learning), which moves the organizational culture of the company closer to the "edge of chaos" (Carley, 1999 [16]; Pascale, Millemann, and Gioja, 1999 [37]). The organization is more adaptive and better learning at this point, and this gives it more of a chance to survive as a group (Carley and Hill, 2001[17]). If it fails to do this, its constituent agents will move on to different groups (given enough employment possibilities) and add variety to their new group, as discussed above.

Some economic models rely on heterogeneity of agents and mirror such conclusions, like the work by Melitz (2003) [67].

In the foregoing description, organizational failure can be beneficial because it releases agents to other groups that are hopefully better equipped at this juncture in time. However, it follows also that each organization fails because of some specific circumstances in its ecology (e.g., Blackberry) and (in general) not from some type of generalized low capacity for success (e.g., UK public rail system; Cyprus banks). Survival does not signify a generalized better "health". A bank that survived a financial crisis can still be defenseless against fraud. A software company that was very successful in developing operating systems for PCs might still stumble in with tablets or smartphones (e.g., Blackberry and Nokia). There is a large path dependency here. The amount of control that a CAS has in determining its own future when multiplicative interaction (connectivity) effects instigate extreme events is much more problematic, if not actually

 ISBN: 978-1-61208-341-4

reduced (Anderson, 2006 [68]; McKelvey and Andriani, 2010 [69]; Andriani and McKelvey, 2011 [70]).

In biology, there is no control at all. Survival is random from accidental ability to survive certain threats. The control among human agents comes from their intentionality (we do not want to enter into a discussion if this is real or just an illusion, it makes no difference for this discussion.) Jack Welch, former CEO of GE, is a good example of CEO who created tensions to motivate managers and employees to seek better solutions by changing their objectives and learning from other executives and/or employees (often newly acquired by "M&A" activities), along with various additional complexity elements so as to get employees, departments, divisions, and companies operation closer to the edge of chaos (McKelvey, 2010 [71]).

Computational Simulation [agent-based computational models (ABMs)]: ABMs allow computational simulations when details of the schemata are sufficiently specified. Many models that can be analytically analyzed have chaotic regions [caused by too many connected variables (degrees of freedom)] in the phase space—like the "melting zone" (the Region of Emergent new Order between the Edge of Order and the Edge of Chaos) in Kauffman's (1993) NK-model [2]. Mathematical optimization models work well below the Edge of Order (in the Region of Order). However, instabilities are expected once the system being modeled tips over the Edge of Chaos.(Canuto et al., 2005 [72]; Bruun, 2006 [73]). Averaging over coordinates of the phase space that are judged irrelevant (coarse graining) reduces the degrees of freedom and makes optimization models more feasible. Incorporating feedback mechanisms (intermediate changes in the schemata made by the agents), and other smoothing mechanisms can handle numerical instabilities that are otherwise unavoidable in chaotic regions, which is to say, get the system out of chaos and back into the Region of Emergence.

In realistic ABM simulations, one would also attach probabilities to some of the options that an agent has, because one could not be sure what an agent would do, given the imperfect knowledge an agent has about other agents. This would also require an ensemble-averaging by making many simulation runs (usually somewhere between 250 and 10,000 runs of the same ABM design to get the average). ABM simulations allow the exploration of interesting areas of phase spaces that current management theories do not probe. For instance, does cognitive dissonance play a role in principal-agent issues? ABM simulations make it possible to formulate hypotheses that can be empirically tested and go beyond the over-simplified math-based optimization models that characterize standard management science by making less rigorous simplifications.

VII. CHECKLAND'S SOFT SYSTEM METHODOLOGY

The Soft System Methodology (SSM) of Checkland (2000) [74] and co-workers can be understood as an attempt to transfer diagnostic tools from "hard systems" as much as possible to "soft systems". Hard systems are those that can be observed from the outside and the dynamics measured with arbitrary precision limited by technology or physics. Hard systems are diagnosed with instruments via observations. Such observations provide a snapshot in time about the system. Experiments can probe its dynamics by disturbing the system.

We assume that there is one (or in any case very few) observers in an organizational CAS who want to know system-wide properties. Most agents will be satisfied with local observations because their dynamics are more determined by these. Others do not have the access or the tools, or do not have the impetus. Managers, who are the administrative leaders in the formal organizations, usually make such more system-wide observations because they need to confront "messy" or "wicked" problems that do not have a "best" solution. At best, managers can develop "approximate" solutions, which may be improved over time—usually in changing environments in which no single, permanent solution is possible, relevant or desirable.

Some of their diagnostic tools are:

- Agents' own observations of the system dynamics: This entails a shift to an interpretive stance, as the observing agent has usually no means to validate its observations in an objective way. (This relates to the postulate in the schemata that no objective knowledge is possible for an agent about another agent)
- Possibly objective observations like business statistics, stored computer records, and so on. These data usually require interpretation as well.
- Ask other agents for their observations. The Soft Systems literature calls this "collecting worldviews". Diverging worldviews are a hallmark of a messy problem. Such messy problems are typical for open systems, because these provide the adaptive tensions that create such "messy" problems.

In principle, the Checkland's soft tools could be applied to a larger organization, but in practice, they do not scale up sufficiently—they are overwhelmed by too many degrees of freedom. In a small subsystem, however, Checkland's SSM approach may offer different worldviews than can shed light on smaller scale messy problems.

The insider/outsider problem boils down to the impossibility for the manager-agent to hold the two measurements resulting from using different diagnostic tools in its mind at the same time. It is not fruitful to consider this as a deep epistemological problem as is sometimes done in the literature. It is just observing the system from two different positions. There is no mystery in that the two views do not coalesce and that looking at a system from two

 ISBN: 978-1-61208-341-4

different points of view with different diagnostic tools does not give a consistent description.

The process of collecting worldviews and possibly get to some convergence among stakeholders, amount to a snapshot and does not lead to new knowledge about the dynamic properties of the system. However, it is more cognizant of systemic issues than most other business and organizational science. On the one hand, an ABM allows the mixing of different views in different contexts to search for the best-at-the-time perspective. On the other, the ABM allows a manager to search for the parts of systemic issues that are essentially the same across the system vs. those that are demonstrably different.

VIII. ACTION RESEARCH

The only way to learn something about the dynamics of a system for which there is no mathematical model is to look at the effects under disturbances. Such disturbances can come from the environment. Much research has been done in observing shocks to systems; most case studies fall in this category. Only via experiments can one alter the disturbances affecting an organization. But we can't put organizations into laboratories. ABMs, however, allow to simulate organizational phenomena and then conduct simulated experiments.

Alternatively, manager-agents can sometimes apply more controlled shocks themselves. This provides an interpretation in CAS terms of the work of Lewin (1946) [75]. Applying shocks and studying scientifically the resulting changed dynamics is, in this interpretation, Action Research. Managers can apply Actions themselves, but it makes sense to first learn as much of the system as possible. One tool is SSM.The problem with SSM is that the static snapshot is little predictive about the dynamics, and so can lead to unintended and unforeseen consequences. But again, doing this in real time with real people could have negative consequences. Safer to use an ABM.

This provides a useful demarcation for what should be called Action Research and what not. Action Research is the scientific study of the dynamical properties of systems by applying shocks in a controlled way and studying the results in an accepted (quantitative or qualitative) way. This criterion, compatible with Checkland's, is very different from Coghlan's [76], for instance. One of the most important points of difference is that our and Checkland's research see CAS and Action Research as (descriptive) science and not as a tool for emancipation or other ethically driven goals. Such goals are possible and compatible, but they are not part of a scientific description. As an alternative for direct observation, this one can do with ABMs.

IX. CONCLUSION AND OUTLOOK

We have shown that it is possible to give a transparent account of CAS with human agents as the indivisible smallest elements that account for most of the characteristics of organizations as they are discussed in management science. This clarifies the relationship between biological CAS systems and organizational ones.

Similarities as well as differences between the models are very important.

- Business agents are inherently less homogeneous than the agents in biology, making fractality much more prominent in business systems. Business agents are constantly adjusting their behavior over a much larger range than in biology, where phenotype behavior is generally set by genotype. Consequently:

- Dynamics is less predictable in business system because of the many degrees of freedom. ABMs become the more relevant method since they offer modeling options and results across a much broader range of interaction effects and nonlinear dynamics resulting from connectivities among some number of heterogeneous agents. Math models cannot be successfully applied to such phenomena.

- Timescales are much smaller. Biological evolution plays out over hundreds of generations. Businesses change at a scale within the lifetime of many organizations, and business adapt. This is possible because of much faster learning in human than in most biological systems, where most evolutionary change is due more to the genetic structure of offspring than the learning abilities of living phenotypes (Darwin, 1859 [77]), though many biologists now place some emphasis on "organic learning" (i.e., learning and change during a phenotype's lifetime (Baldwin, 1896 [78]; Simpson, 1953 [79]; Crispo, 2007 [80]; Badyaev, 2009 [81]; Kauffman, 2013 [82]; Scarfe, 2013 [83]). Survival in changing environments is a function of learning quickly as needed in addition to surviving because of genetic, structural or endemic advantage.

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