Control Criticality within High-Complexity and Low-Threshold Systems, and the Role of Topological Quantum Computing in such Solutions

Martin Dudziak[1,2]

[1]Institute for Innovative Study, Washington DC
(Tel : +1-202-415-7295; E-mail: martin@instinnovstudy.org)
[2]Department of Aerospace Engineering, South Urals State University, Chelyabinsk, Russia
(Tel : +7-925-161-6713; E-mail: martinjoseph@mirnova.org)

Abstract: A confluence of natural and social factors creates an environment rich and also problematic with non-deterministic systems characterized by high uncertainty, noise and asymmetry in behaviors and predictability. Natural influences include environmental and climate changes and the growth in space-based mechanical activities including new deep-space ventures such as asteroid mining and impact-deterrence. Socioeconomic developments include the pervasiveness of internet communications and devices ("Internet of Things" proliferation of personal and industrial appliances) and the growth of cooperative and interactive robotics, as well as self-driving automobiles and trucks. Increasingly our society is engaged with both desires and needs to exercise control over systems that are extremely complex and also have low thresholds for failure. New models for computation are required which can go beyond the constraints of conventional Turing-machine calculators, including massive parallel machines and prospective quantum computers that employ discrete qubit logics for superposed representation of binary values in the same framework of computation-as-calculation. Topological computing based upon a fundamentally biological model offers promise for delivery of physically and operationally robust computing machines that will serve the requirements for intelligent control and cybernetics in the management of increasingly complex and "extreme" systems.

Keywords: control, cybernetics, machine learning, artificial intelligence, complex systems, quantum computer, self-organization, topological models.

1. INTRODUCTION

Complex systems are characterized by time-varying structures of the state space which may be linked to changes in the operating environment and in non-linear dynamics within components of the system involved. The general goal of building a representational model that can be employed in controlling such a system is to have adaptive capabilities that can respond to anomalies, asymmetries, and critical events. Intelligence in the most general sense involves look-ahead modeling, prediction of some course of decision and action which will alter that state space in a manner that is consist with a set of goals. As systems become more complex in dimensionality and as both uncertainty and nonlinearity increases, deterministic control models and traditional computational methods have more limitations and more potential for falling into singularity or catastrophe types of critical states.

"The mathematical description of the world depends on a delicate interplay between continuous and discontinuous (discrete) phenomena. The latters are perceived first. 'Functions, just like living beings are characterized by their singularities,' as P. Montel proclaimed." [1; Introduction]

A class of problems that typically involve or lead into singularities are not solvable exclusively or even typically in a linear fashion, such as by increasing clock cycle speeds and numbers of processors. Nor is the solution set realized only by dividing computational loads among the virtual-processor model of certain quantum computer architectures that are still based upon the Turing model of finite series of instructions, regardless of the parallelism employed to achieve a final and optimal choice among n alternatives.

One desirable solution exists with strong evidence from success in different applications for environments where the regions and thus the parameters of interest and requiring attention are not predictable. Such a solution type can adapt to dynamic environments where state space changes may reorient the relationships of different critical parameters to one another and to some key constraints (e.g., limit points in power, temperature, pressure, stress, etc.). This poses unforeseeable problems for a unitary model where structure and the computational processes applied to such a model may not be sufficiently flexible. The costs can be omission of anomaly conditions (the classic "1% unlikely probabilities") or a computational overload that makes working with the model unwieldy or impractical, particularly in real-time, micro/nano-scale, and long-distance (e.g., light-minutes of physical distance) situations.

The new method is to replace the general "unitary" model of interaction with a complex system Φ - whereby some model M is consistent over time and unchanging in its internal structure and the algorithms by which it is measured and employed, with respect to the primary system of observation and control of Φ - with a different schema of modeling. What changes is the “model of the models.” The method is based upon viewing the system Φ in terms of a collection (“field” or “space”) of local cellular regions and employing a generalized stochastic, randomized procedure of evaluating and measuring such local regions and their parameters, with respect to the control objectives – the cybernetic teleology or goal-set – for system Φ [2].

In fact, the goal-sets for Φ may change, as well. But as a rule these will be fairly constant based upon how Φ is designed – or, in the case of natural systems (e.g., organic metabolism, climate, planetary dynamics, stellar physics) how we define and delineate our understanding of these systems.

In this alternative approach, there will be multiple local models $M_{(\Phi)[i]}$ that each focus upon a particular limited set of parameters or a finite and dimensionally-localized region of the state space of the system (Φ) they represent. Together they can be thought as comprising a set of models S = {$M_{(\Phi)[i]}$ ...} which at any given time, or some other demarcating condition (e.g., when certain parameters are in particular ranges of value, or in particular ratios with respect to one another), will be applied for the purpose of representing and controlling Φ.

Each local model $M_{(\Phi)[i]}$ is effectively a cellular region or network within the state space of Φ. They may be abstractly considered as neighborhoods (bounded strictly or loosely in 2, 3 or potentially n dimensions), very much in keeping with cellular automata theory [3,4]. Alternatively, they may be viewed as a type of “perceptive window” into one facet of how the system Φ is behaving at a given time or interval and in relation ship with other components (subsystems). These local models may be used in a manner of aggregation (clustering) which is not itself static; i.e., the scale of the local model parameter space and the methods by which such models $M_{(S)[i]}$ are aggregated and considered together, may itself vary over time and be influenced by the prior history of the system Φ and – importantly – the knowledge that is acquired and learned by the control system during that history [8].

In Section 2, the limitations of conventional cybernetic methods for emerging “extreme” types of complexity are discussed, along with reasons why many current computational machines (including very “fast” calculators) cannot in principle suffice for the types of tasks such systems and their models require. This is essentially what may be termed the “Turing Barrier” and in Section 3 it is shown how this limitation applies also to qubit-based architectures, so-called quantum computers. In Section 4, an example is presented for such local region division and clustering, based upon analysis of aerodynamic turbulence and and how physical systems such as airplane wings can be treated as sets of local regions that are clustered together in different set combinations in order to determine the optimal changes to a mechanically controllable surface. The goal of such a system as an aircraft is to maintain stable and consistent flight and to complete its missions, also with optimization of safety, physical integrity, and fuel consumption. The process of analyzing all relevant parameters in order to make changes to specific components (e.g., wing flaps and ailerons) during the onset and duration of extreme and sudden turbulence is an example of an NP-hard problem for which the Turing model of computation, and the classic deterministic method of modeling, does not provide sufficient power. It is not a question of simply adding supercomputer or quantum Turing-computer (QTC) resources. Rather, the wing in this case must be viewed more like how the wings of biological flying machines – birds – adapt to turbulence. Feathers evolved with a functional purpose. (This will be discussed further in Section 4.)

Moving to Section 5, the argument proceeds to the what-and-how of a radically different model of computation that is contoured, physically and logically, to fit the requirements of rapid, virtually instantaneous sensing and reaction to critical changes in even vastly displaced and dispersed systems, for adaptive and heterogeneous introduction including “discovery” processes, that can better model, adjust, optimize, and control such systems. The foundation of such in what are arguably the best examples of “natural computing” machines that can be used as examples and starting points, and these are none other than biological organisms – “living things” themselves [9,10].

2. GENERAL LIMITATIONS OF DETERMINISTIC CONTROL FOR EXTREME SYSTEMS

Extreme systems can be of many sorts and types. In Figure 1 below, a map of the world of today and tomorrow is presented in terms of complex systems that have extremes in several aspects, internally and with respect to how these systems are employed in society and in what are the consequences of failure.

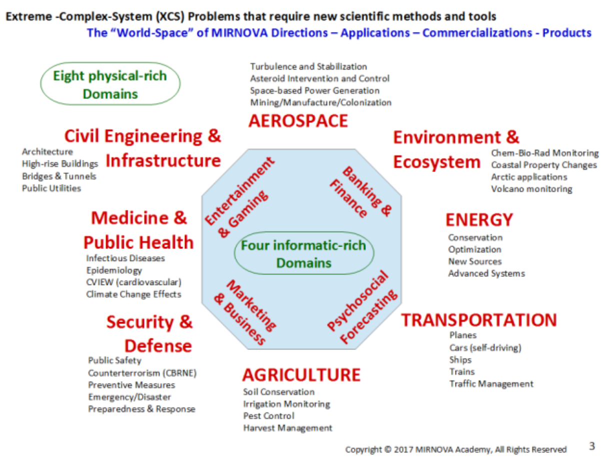

Fig. 1 Twelve Domains of eXtreme Complex Systems with high uncertainty and non-linearity

The special attributes of interest, within all of these domains, both physical-centric and information-centric, are their disposition to high and unpredictable levels of uncertainty, noise, and non-linearity. One may also add that all have multiple criticality points, singularity regions (catastrophe zones), for which there can be rapid changes in one or usually several key system parameters that can thrust the system into such a singularity (catastrophe) condition.

2.1 Consequences and Limits of Classical Models

Mathematically interesting in any case, singularity or not, these are systems on which lives depend, from individuals to entire species and planetary populations. Consequences can also be extreme. Thus, humanity as a species is continually and necessarily pre-occupied with managing such systems which are now part of the essential infrastructure. In some cases humanity has become habituated to behaviors that make the extreme values into life-critical ones – such being the case with those domains of activity considered as economic, military, energy and healthcare. “Failure is not an option” has become a very real rule.

Automation, calculation speed (clock-cycles, multi-threading and other forms of parallel processing) and the continued growth of learning capabilities (“AI”) within control systems, are all among the ways by which many of the XCS in today's world are increasing in their capabilities, diversities and obvious control-ability. The versatility and efficiency of different mechanical robots has led to a proliferation of diversity and the emergence of cooperative networks involving robots as well as human-robot teams, thereby compelling arguments to introducing more robots and more AI (artificial intelligence) – and more complexity and nonlinearity in the process, into these critical infrastructure systems.

However, there is the matter of the “Black Swan” conditions and consequences, the “1% or less” outliers and unlikely anomalies [11]. There are also vulnerabilities that derive from unavoidable exposure of such inherently high- dimensionality systems and their critical parameter sets into the social sphere. Any system with inputs and outputs into others is not a closed system physically and thus informationally. Any system can be tapped and tampered with. Risks of system instability and criticality are further exacerbated by conditions that can be introduced from external agents and unpredictable configurations into which even a well-designed and well-tested system (e.g., aircraft, rail, satellite, wireless network) may be placed. External-origin disorders and failures increase in relation to not only complexity within a control system model and its physical and computational implementation, but also in response to other paths to vulnerability. This concerns not only cyberthreats in the vernacular sense, but the impacts of natural and accidental disorder that can enter into a delicately balanced and essentially hard-to-model system which can come from a power outtage or surge, an EMP event, or simply a component breakdown.

A further issue concerns emergent and unplanned conflict and “un-cooperativity” within complex multi-agent networks; this may range from classical resource-thrashing to direct conflict due to unforeseen convergence of competing goals and insufficient solutions being built into the control logic (e.g., overriding rules and heuristics) for resolving such conflicts. This is not only a matter of higher-level cognitive-type reasoning functions in machines (as with people) but very basic sharing and distribution of resources such as energy (fuel, accessory equipment and supplies, etc.). This can also be described in terms of load-balancing problems, but the problem becomes more complicated as autonomy and independence of the agent subsystems increases.

Outcomes for end-users (passengers, patients, bankers, communication networks, civil engineers) may be quite more severe in cases of critical mechanical failure, incidents of cyberhacking, or system critical points and singularities that were not projected during the design process. Supercomputing, high-bandwidth and AI can offer a “double-edged sword” in many respects – improved or optimal performance and beneficial results, when everything is running smoothly, or else true “crash and burn” catastrophic results, which from experience are generally more severe because of being less unexpected. A fall from a stair or stool can be a more severe injury than a fall during a martial arts competition; a spill at the dinner table can make more of a mess than while working at the kitchen sink.

All these issues become even more delicate and potentially severe in impact when operations are conducted in remote environments such as orbital, lunar or interplanetary space, in deep-sea environments, or in mines (where robots are now being employed). These types of XCS operations, with and without mobile robots, are increasingly “omnipresent” in our society and economy. However, the majority of critical robotic tasks, to date, have been generally limited to singular-function (even composite) devices (e.g., satellite or landing rover) with limited variations in the type of interactions that may take place. As complex as have been missions to Moon, Mars, Jupiter, Saturn, 67P/Churyumov–Gerasimenko and other destinations, operations involving two or more robot devices interacting with each other and/or with manipulation-type operations (e.g., involving other objects such as an asteroid or a fragment of space debris) have been limited. Moreover, command and control involving human operators has been highly constrained in order to accommodate signal transmission delays as well as periodic and asymmetrical breaks in uplink or downlink. However, the standard channels for human control of objects that may be physically “incommunicado” (either perpetually or at certain intervals due to distance or other physical barriers), is inherently limited.

2.2 Complexity control requires more flexible models

The "demand portfolio" for increasing complexity, autonomy, and central criticality (in the sense of human dependency upon such systems) alters requirements for intelligent, adaptive, and fault-tolerant control systems. Deterministic models cannot work satisfactorily when parameters cannot be identified, measured and estimated with sufficient certainty. This critical claim is directed also at such quasi-deterministic models which include Bayesian probabilitistic networks, neural networks, and other variants of both statistically-based and rule-based "machine learning."

If the control system for the state-space of some target system Φ has only one model $M_{(\Phi)}$ or even if there are multiple models $M_{(\Phi)[i]}$ (local or global, as alternative choices under some hierarchical logic or a "previously trained" pattern learning system (e.g., neural net, generic algorithm, Bayesian net) then the impact of disruptive changes affecting the mapping of any fixed-parameter-set $M_{(\Phi)[i]}$ to a changed state space of Φ can have unpredictable error consequences. These may be reflected only in computational performance loads and time to complete tasks, but those can also have catastrophic impact upon Φ overall, particularly in real-time and remote physical operations.

It is thus argued here that a new type of thinking about command and control is necessary, and with it, a new type of computing architecture as well, for the types of machines and systems that offer such dual-impact concerns which may be termed "Extreme Complex Systems" or XCS. However, this new cybernetics and new computation is not simply a move into multi-agent parallelism, which is still inherently deterministic (in most architectures; Figure 2). We suggest, on the basis of formal and experimental results, that stochastic, randomized, and non-parametric-dependent modeling may be often more effective for stable control of such XCS environments.

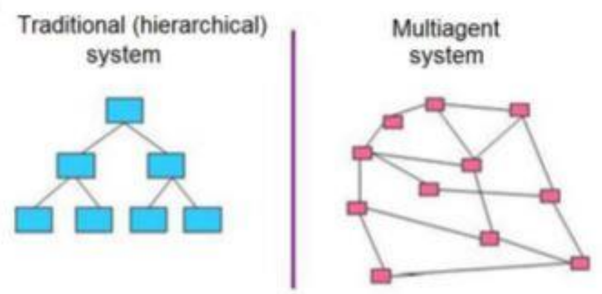

Figure 2 --- Hierarchical vs. Multi-Agent Control - but still deterministically based [13]

We make a distinction here from other forms and levels of complexity in both natural and artificially-engineered systems. By XCS we mean those types of systems which are inherently hard to formulate into models and algorithms to process such models, by virtue of the uncertainties and stochastic, random-like natures of their parameters, and through the complex relationships and inter-dependencies among those parameters. Computationally, these may be NP-hard problems, but not necessarily so. Instability and insufficiency within a given control system may be not only due to the calculations that must be performed in order to ascertain values and even value ranges for such parameters. Limitations on physical hardware and long-distance communications, for instance in aerospace as well as high-speed rail, subsurface sea, and high-density highway traffic, curtail the ability to perform calculations that even in "polynomial time" may vastly exceed the time limits for answers, for decisions on course correction.

An XCS environment can be considered as having an unknown and uncertain structure, where that structure s_k changes in time instances $t_0, t_1, t_2, \ldots$ The task of understanding how s_k changes at specific instances t_i and in response to certain parameter changes may not be computationally achievable, certainly within finite time intervals when change (adaptation) is required in order to avoid catastrophic critical values. There are in fact three major issues, all of which demand a change to the usual structured, deterministic algorithmic thinking:

IF the structure s_k changes in different time instances t_i, and IF the changes within s_k are varying (within different parameters and combinations thereof, and IF the stimuli, the parameter changes that trigger the s_k structural changes may vary in their attributes and effectiveness (e.g., p_i and p_j are parameters which must both change by some factors k_i and k_j, but only under certain "other" conditions which are empirically "masked" from observation and not known within a control algorithm,

THEN there is an inherent limitation to using a control algorithm that is based upon not having such changes occurring but instead positing uniformity and consistency and a "completeness" that in unattainable within the confines of the algorithm [14].

The path forward to understanding how changes and how to adapt in terms of a control system may be realized by a technique of dividing the state space into regions, clusters, or cellular networks. Clustering of the state space may be understood as:

$$X_{sk} = \{X_1, X_2, \ldots, X_{n(sk)}\} : X = \cup_{i=1,2,0\ldots,n(sk)} X_i,$$
$$\text{where } X_i \subset X$$

The change in the structure of the space states (including dimensionality) is possible in the medium when clustering changes in response to disturbance factors which may act as triggers influencing a change in how the local cellular neighborhoods are defined and also how these clusters are measured with relation to others. In other words, adaptation to structural changes can occur through modifications (a) in the choice of some model $M_{(\Phi)[i]}$ from a set of such models, or (b) in the definition of a given model $M_{(\Phi)[i]}$ or in both (a) and (b). Computationally, this can be implemented in "multi-agent" paradigms with parallel processing architectures, including conventional multi-threading, but for which MIMD architectures can be more suitable.

Note that external perturbations in system Φ can occur due to internal self-organization, as in many multi-agent systems. In the presence of coherence in the behavior of certain groups of agents, the overall dimension of the state space decreases. But perturbations can lead to decoherence and a violation of the consistency of the behavior of agents in some group, resulting in an increase of the state space dimensionality.

The goal from a cybernetic perspective becomes then one of identifying changes within dynamically defined regions or clusters, making use of simplified sampling and adaptation, avoiding the computationally intensive and deterministic methods which can be less resilient to unexpected and non-linear behaviors, and impractical from the standpoint of practical engineering, especially in the case of microscopic-sized or ultra-light devices.

3. LIMITATIONS OF QUANTUM TURING MACHINES

The contemporary quantum computer that is based upon a qubit-array architecture, regardless of its physical implementation, is derived from a quest focused upon two algorithms, the Shor factoring problem and the Grover sorting problem [5,15,16]. Both of these tasks are challenges to conventional Turing machines because of the numbers of numerical calculations that most likely need to be performed before an answer is achieved. There is without any doubt a special-case need and place for such numeric-intensive processing, comparable to the obvious advantage of floating-point (FPU) logic in a conventional CPU over simple arithmetic (ALU) logic, or the advance during the past three decades into graphics processing (GPU) specialization.

Fig. 3 Basic bit vs. qubit representation

In the qubit-based Quantum Turing ("QT") machines, there is still an adherence to the Turing paradigm of defined, discrete values for the elements assigned to represent data (as operand or operator), and thus to be preserved during the duration of the computational process − regardless of the fact that as a qubit there will be a superposition-state of at least two values ("1" and "0" or "spin-up" and "spin-down") for some initial value-element. As a result, coherence of the complete entanglement space is critical for the duration of the computational cycle [17, 18]. There are well-known engineering issues pertaining to noise and decoherence (the bane of maintaining the quantum entanglement states for sufficient periods of time in order to complete the computational process). The tentatively explored solutions to the decoherence problem have system infrastructure consequences (e.g., physical size, mass, and power requirements) that at least for the foreseeable future may render QT machines as impractical for many missions such as space robotics and embedded micro-scale systems) [8].

However there may be more fundamental limitations to how the QT machines of the future (on the fair assumption of engineering solutions and reliability) will be able to address the type of XCS that have been considered here in this paper, where the very nature of the state space can change and be significantly altered in ways that may be both unpredictable in advance and unpredictable in timing and occurrence.

This is the dual-faceted issue of static versus dynamic representation and structure in memory and static versus dynamic distinction between data and process or what is typically referred to as program or instruction-set. In the QT architectures to-date, the element topology within the qubit array is fixed and an algorithm is mapped into it. A finite set of operations is performed according to the initial definition of the algorithm and this includes the bounds of each element of data and instruction-set which do not (should not) change during the course of computation. For the hypothetical system Φ this amounts to having a static set of one or more models set of models S = $\{M_{(\Phi)[i]} \ldots\}$, each of which is based upon a fixed subset of parameters in the state space of Φ. However, if the boundaries and even the dimensionalities of these models change, as a result of the dynamics within Φ, these will not and cannot be reflected into changes in any given model $M_{(\Phi)[i]}$ that is being evaluated within the QT machine.

For the duration of its process life-cycle, the QT must remain a "black box" and allowed to reach its final state; this is true for not only "quantum annealing" type designs but other types of QT machines [19]. The implication is that the QT machine designs of today and their hopeful implementations as physical computers of tomorrow, will serve a function of potentially much faster numerical calculations for specific problems, similar to factoring and sorting, but their ability to address the previously discussed "primal issues" of XCS will be not that much different from current conventional Turing machine computers [8, 21].

The principle challenge with XCS remains, and this is the issue of undecidability about critical points and regions, also known as singularities. A general or comprehensive model of interaction within distributed and non-stationary spaces that does not allow for the appearance and even dominance of critical points can lead to catastrophic results (mathematically and physically). Failure to observe minute variations and gradient changes can lead to irreversible situations. However, such minute variations may be measured and analyzed much faster through attention to local neighborhoods and cellular-type regions or fields of data. This path has led to new approaches using sets of localized models with simpler and potentially faster computational loads and more conveniently mappable to parallel architectures. Such models are characterized by asymmetric, stochastic methods for sampling, estimating, and assessing predictive values for regions in a data space where changes may otherwise be unobserved within constraints of computational time.

4. AN EXEMPLARY MODEL (AEROSPACE TURBULENCE)

Stochastic programming is one framework for modeling of optimization problems that involve uncertainty in both the identity and interrelationship of parameters and in their values at given instances and configurations. Whereas deterministic optimization problems are formulated with known parameters, real world problems almost always include some unknown parameters. One of the approaches for solving such problems, when the parameters are known only within the certain bounds, is called the robust optimization. Here, the goal is to find a solution, which is feasible for all such data and is optimal in some sense. Stochastic programming models are similar in style, but take the advantage of the fact that probability distributions governing the data are known or can be estimated. The goal here is to find some policy that is feasible for all (or almost all) the possible data instances and minimizes the expectation of some decision functions and the random variables. More generally, such models are formulated, solved analytically or numerically, and analyzed in order to provide useful information to a decision-maker. The approximation techniques are then extensible to randomized selection and trial (an interpolation process) of algorithms for adjusting system parameters (Figure 4). In the experimental case described here, this randomization is performed with a pressure-actuated control model directed at making a topological-based response to unpredictable variances in pressure across a wing surface, such as in an airplane wing. The goal is to identify field-like, wave-like surface (topos) disturbances faster than by adherence to deterministic methods of data acquisition and analytics.

The Local Voting (LV) control protocol developed by Granichin et al [13] is one such model. It operates with a nonvanishing step-size for conditions of significant uncertainty and external disturbances [13, 20]. The objective is to detect changes that may be insignificant in most cases but which can be indicative of developing conditions leading to irreversible effects. Stochastic gradient-like (stochastic approximation) methods have

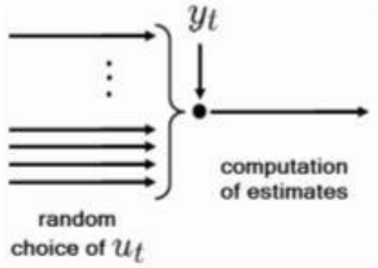

Fig. 4 Random selection of estimation and control [13]

also been used before in other works [12,20] but with a decrease to a zero step-size. Usually, the stochastic approximation is studied for *unconstrained* optimization problems, but the above-mentioned results stimulated the development of new approaches [13c] to track the changes in parameter drift using simultaneous perturbation stochastic approximation (SPSA) [2].

An experimental platform has been developed [12, 13] (Figures 5-7) which addresses one major problem in aerodynamic stabilization during turbulence, focusing upon wing surface pressure points as the key observable parameter. The wing surface is covered with actuators that serve as mini-wingflaps, each coupled with a pressure sensor, such as illustrated in Figure 5. Each sensor-actuator unit may be considered as an active agent in a computational network. However, sampling – and motor response – can be performed asynchronously and asymmetrically – this derives from the use of the stochastic approximation methods. This may be considered as a prototype for use of the LV protocol to other applications including the interactivity among a group of cooperating robots. In other cases the “turbulence” is not present in a classic aerodynamic or hydrodynamic phenomenon but there are comparable dynamics in the forces exerted between the target object and the robot apparatus operating with it.

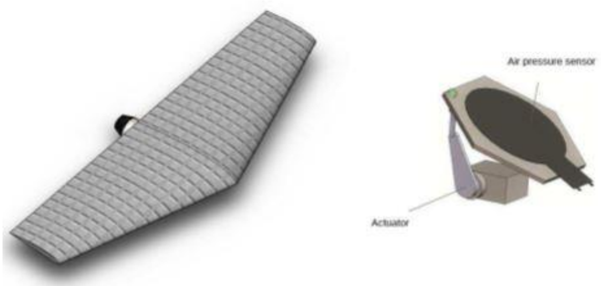

Fig. 5 “Wings with feathers” [12]

Let x^i_k be the integrated pressure deviation for “feather” a^i – data derived from sensor measurement. Agent dynamics may be described as:

$$x^i_{k+1} = f\,(x^i_k, u^i_k),\ i \in N = \{1,...,n\}$$

Observations: $y^i_k = x^i_k + \xi^i_k$

The Local Voting Protocol is given by:

$$u^i_t = \alpha \sum b^{i,j}_k\,(y^j_k - y^i_k) \quad \text{where } j \in N^i_k$$

Consistent behavior (consensus): $x^i_k \approx x^j_k$, $i,j \in N$
In a turbulent flow environment with no responsive adjustments to sensor-actuator units, LV readings across a wing surface resemble a "kaleidoscope" effect among the regions, as shown in Figure 6 below. All actuator units "feathers") in the wing remain unadjusted and with no change in orientation in response to changes in applied external pressures. The consensus "goal" state (cf. Fig. 7) provides for uniform or within-threshold values from all LV "cellular regions" (clusters) during turbulent conditions, achieved through servo-controller adjustments of the sensor-actuator "feather" units.

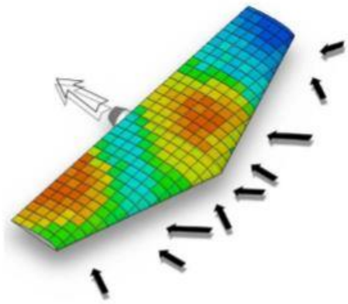

Fig. 6 Wing sensor field under turbulence [12]

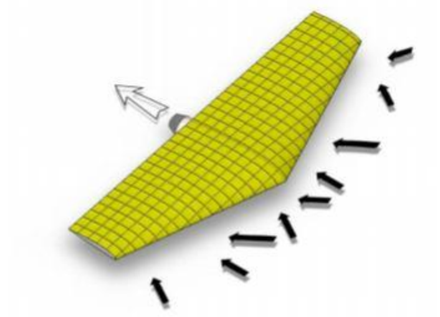

Fig. 7 Wing consensus state under turbulence [12]

In this given experimental case, LV clusters are statically defined by the geometry of the sensor-actuator units (Figures 6 and 7). Stochastic approximation and randomized sampling and perturbation is not limited to a static architectural model of the given system, but rather, a conventional aircraft wing, and the entire vessel, constitutes a static geometry – the wing has a defined and permanent geometry. In other applications and tasks the LV regions need not be uniform, nor static, in their geometry. For instance, consider cooperative agents working with interchangeable components (such as tool fittings) in physically dynamic environments with unpredictable kinetics (such as an asteroid in the process of being mined or split into fragments with the intention of reducing impact threats to Earth or some other habitation). It is possible to create different "dynamic" maps of LV cellular regions and also larger assemblies of clusters, with different geometries that correspond to how the system is being affected by its environment at any given time period.

Within XCS operations there are critical time intervals for such adaptations that can avert an critical "singularity" event affecting the entire system. Adaptation of wing surfaces (and potentially also other components) in an aircraft to sudden turbulence requires asynchronous adjustments of multiple actuators. Randomized alterations to small regions (clusters) of the system space have two unique advantages over models that attempt to comprehensively address the entire system. First, results can generally be achieved faster and with fewer computational resources. Secondly, and very significantly, errors in the decision process – which can be frequent in beginning stages of a cybernetic system adaptive learning process – will be more localized, more containable, and more easily correctable, than errors that affect large sectors of system performance. Drawing from the illustration of wing adaptation to turbulence - adjustment of several "feather" actuators, in a way that has an adverse or otherwise non-beneficial effect on the overall system, will (generally) be more easily correctable and offset by other adjustments, in contrast to a system-wide adjustment that may be irreversible.

5. TOPOLOGICAL COMPUTING MODEL

A topological information resonance (TIR) model of computation is introduced as a "model of modeling" XCS, by treating a topos or whole surface as a unitary entity that can undergo a variety of surface changes which will be reflected into the choice of the local cluster nets, the neighborhoods, that must be examined and processed within an LV protocol. This in turn allows for changes (selections) in the parameter sets defining one or more models $M_{(\Phi)[i]}$ that determine the relevant state space parameters which are dominant in system Φ dynamics. This computing model is heterogeneous − it employs Turing calculations and processors, but it also incorporates a design that uses the mapping of physical changes in a topology of a surface which acts as the model for system Φ. That mapping governs the distribution of tasks among any other computing resources of different types [21].

This TIR model operates analogously to the wing surface consensus that is built from randomized evaluations of local cellular neighborhoods across a finite surface. As a general "machine" that can be employed for multiple "topology mappings" of abstract system states, the current thinking is to employ a molecular construct that can be conformationally altered through nanostructured node-elements added to a protein or nucleic acid base framework. The nodes respond electromagnetically to measured changes in the external system Φ parameters.

This direction of thought leads toward a physical device (currently the subject of experiment as a molecular array of protein-polymer conjugates) that is subject to quantum-scale effects for its operation, including entanglement states between numerous (and an indeterminate and indefinite number at a given instant in time) node-elements (e.g., quantum dots along the macromolecule chain) [22]. Unlike QT devices, this use of entanglement will not be so strictly bound to particular memory-value locations, to specific dots or nodes, and the natural decoherence of many entangled states within the overall topos-network will not be the problem of the scale that such noise-related decoherence is with QT machines. Thus, it is expected that the TIR machine will enable non-Turing or trans-Turing computing functions in a manner not possible with any possible Turing machine. Without limits of static digital memory and processing instruction values, this can provide an answer to the limitations of conventional and QT computers. The molecular substrate that topologically reflects the states of all models within S = $\{M_{(\Phi)[i]} ...\}$ that represent a system Φ; each such model is real-time constructed from the geometrical coordinates of the topos formed by conformational changes in the molecular array [21].

The TRP is currently projected to be capable of operations in ambient environments (e.g., "room temperature"within thresholds of -10 C to +40 C) and to require no cryogenics or specialized external support or shielding equipment.

6. CONCLUSIONS

Extreme(ly) complex systems pose critical limits for using control models that depend upon fixed mappings from the system Φ state space to any finite set of models to be employed in controlling Φ. Even contemporary quantum computing architectures are limited by an inherent dependence upon the underlying Turing machine framework of calculations. A topological approach that directly employs and uses indeterminate and uncertain states in its mechanism (structure) can represent more accurately the dynamics of critical non-deterministic systems. Such a topos-machine can tmodel parameters and their relations to one another as segments of a continuous surface (topos) and thus offer a way to detect unexpected changes in criticality sets and their relations to one another. This will enable the more accurate and timely choice of model(s) to be used in controlling Φ in keeping with how the state space is changing. Moving into experimental implementation of such a topological computer is the next phase of work.

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