ON DIFFERENT TREATMENTS FOR DIFFERENT TYPES OF A SYSTEM COMPLEXITY

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Abstract. *A systems view of the world is becoming the main paradigm in modern human practice. And in all practices, the main concern is to overcome difficulties that stem from complexity of a system under consideration. But the "complexities" have various origins of a different nature, and thus require different approaches to tackling each of them. The paper discusses these differences.*

Key words: Complexity, complex systems, types of models, types of complexity.

ON VARIOUS MEANINGS OF THE TERM "COMPLEXITY"

Any word in colloquial language has several (sometimes – many) different meanings. This enables us to speak by finite phrases about infinite variety of the world. But when our practice requires more precise speaking of a specific part of the world, we use only those meanings of a word that have the closest relation to the theme of concern. It is in this way the "professional" languages emerge. Look, for instance, at various meanings of the word "field" in agriculture, physics, surgery, geology, military, sports, sociology, etc.

The terms "complex" and "complexity" are no exclusions. A variety of their meanings in professional languages is the hot theme in systems thinking research and discussions; a reach in content survey of them is given in (*Cabrera, 2015*).

A system is usually called *complex* in cases when one meets a difficulty in dealing with the system, – either when studying and explaining it (investigation, cognition), or when purposefully changing and controlling it (e.g., governance). However, since the difficulties may have various causes, the different types of complexity must be distinguished. It is important to tell the difference between them explicitly and precisely, because systems of different complexity types require very different approaches to their tackling. This is the reason why systems with different origins of complexity deserve even to be named differently, not just "complex". A try to survey certain classifications of types of complexity and corresponding methods of their treatment is presented in the following.

1. A CLASSIFICATION ACCORDING TO DEGREES OF NATURAL COMPLEXITY IN BEHAVIOR OF A SYSTEM

Studies of dynamic behavior of systems described by fully deterministic differential equations (of the second order partial derivatives) have revealed a discreteness of types of its behavior: their trajectories in phase space tend to converge to one of four possible configurations (“attractors”) – consisting of points, cyclic, torus-like, and “strange” one (see, for instance, *Hirsh, 2004*). The discovery of *randomness* of trajectories inside torus and strange attractors became a real sensation. This discovery, together with the fact of limitedness of the attractors number, each with different degree of randomness of trajectories in it, was the Third Great Achievement of the 20th century in cognition of Nature (the first two were Theory of Relativity and Quantum Mechanics).

A vague feeling that this is not just another amazing and beautiful law of physics, but a manifestation of a more general law of nature, was confirmed in studies of chemical, biological, and social systems: similar peculiarities of system dynamics were observed everywhere. In particular, the four types of systems are discerned in government and management: *simple, complicated, complex,* and *chaotic* ones (*Snowden et al., 2007*), – right in order of growing *complexity* of dealing with them (according to the increasing uncertainty in predicting their future behavior).

Certain methods were developed for overcoming specific difficulties connected with the first three types of complexity. These algorithms exploit possibilities to neutralize the particular cause of a complexity: to compensate the lack of a certain resource (matter, energy, information, or time) needed for achieving the goal. Naturally, the different algorithms are tailored for overcoming various sources of difficulty (see, for example, *Tarasenko*, *2010*):

- If the system is *simple* (i.e. all the necessary resources are available) then *programmed control* is used;
- If the system is *complex* (i.e. there is a lack of information about the system) then the *trials-and-errors* algorithm is appropriate (note the specific narrowed usage of the term “complex” in the case of insufficient knowledge of controlled system);
- If a discrepancy between the desired and observed trajectories of a system behavior is “small” and may be compensated by a change of a single system’s parameter, then the algorithm of *regulation (adjustment)* is applied;
- If the discrepancy is so “large’’ that it can not be eliminated by regulating, then algorithms of *restructuring, reorganization* and *perestroika* are applied;
- If the previously planned purpose turned out to be not feasible objectively, then *changing the purpose* for a supposedly achievable one is suitable sometimes;
- If the system is *large* (i.e. there is a lack of time for finding the optimal decision “just in time” because of a large dimensionality of the system which leads to its delayed modeling) then various ways of *quickening the decision-making* are applicable (note again the specific sense of terms “large“ and “small”, distinct from that in informal English);
- If the *final purpose is indefinite* or *unknown,* but a hope still exists that there is a better state of the system, then the *heuristic (revolutionary)* and/or *empirical (evolutional)* approaches are used.

However, the problem of coping with the complexity of *chaotic* (i.e. objectively, naturally random) systems, remains quite different: we can not change the laws of natural randomness of ongoing events. The only reasonable possibility for us is to adapt ourselves to stochastic events going on around us, like sailors do it being caught in a storm, or pilots flying trough air turbulence, or surfers maneuvering along the steep slope of a wave. As Donella Meadows put it (*Meadows,2008*), chaotic systems can not be controlled, but it is possible "to dance" with them along their "pattern" of behavior.

Systems Thinking suggests several methods for work with social systems entering into the chaotic phase of their life cycle. These methods are based on the creative usage of information about the *objective* laws of development of Nature, such as fractality, transitions between archetypes, self-organization, pattern recognition, etc. However, M. C. Jackson, who discussed in details ten systems approaches to problem solving (*Jackson,2009*), warns about a much higher complexity of social systems than that of physical chaotic ones, – which stems from their structure containing not only the *objective* factors but the additional *subjective* ones: humans' conscience and free will, a divergence between stakeholders' opinions, various proportions of empathy, tolerance and hostility between them, quality of communication facilities, etc. … This requires from managers to turn to account of a creative holism and being very cautious in practical application of results of the formal theories.

2. A CLASSIFICATION BASED ON THE TYPES OF SYSTEM MODELS

Purposeful influence on reality (e.g. the control over social systems) is based on information in the working model of a transformed system. Which one of three basic models, – *black box model (list of inputs and outputs), model of composition (list of parts),* and *model of structure (list of connections between parts),* – or which one of their combinations is used as a working model in the particular case, depends on the pursued end. Unfortunately, any constructed model may contain errors and mistakes, and this would create difficulties, *complexities* in the work with the system.

And again, we face a variety of complexities; they need different approaches to tackle them. Let us consider a classification of complexities that may appear in each of the basic models.

2.1. Multidimensionality as one of the origins of complexity

In some cases, the utter information *about all* elements of a system is necessary for successful solving a problem: a full list of all system's components is needed. However, there are systems consisting of a huge number of elements. Processing the whole information becomes complicated if it must be fulfilled in a limited period of time. This difficulty is called a "curse of dimension" or a "big data problem" in informatics community; such systems are called "large" in management. A.N. Kolmogorov suggested (*Kolmogorov, 200*5) measuring the complexity of a large system by the length of the computer program that describes the system completely. A real-life example of "the large system case" was the 3 to 4 years delay in calculating by GosPlan (Central Planning Commission of the USSR) of the annual inter-industrial balance between millions of produced and consumed products. This was one of the causes of poor effectiveness and efficiency of totally centralized governance of the Soviet Union economy.

Thus, the essential peculiarity of this aspect of complexity is the contradiction between the demand to do whole job not later than by a certain moment, and the fact that there is an acute shortage of time for finding the best solution through sorting it out from all possible solutions by means of sequential modeling each of them, – simply because the sum of times for modeling them exceeds the critical time assigned for decision making. Such systems are called "large".

The necessity of tackling this situation may be satisfied in two ways. The first one is a physical acceleration of modeling: to buy a faster computer, to hire several qualified experts for doing parts of the job simultaneously, and the like. But this requires spending extra resources, and in case of their shortage we are forced to use the second way of managing large systems. It is quickening the decision-making by switching from the time-consuming full optimization to the rapid finding a satisfactory, acceptable solution, although it is not the best. A not optimal but timely decision is better than the best one but late. There are two ways to do this. One is to evaluate alternatives in turn precisely, up to the crucial moment, and choose the best one of those already explored, in spite of the fact that the optimal alternative may be among those not yet studied. Another way is to simplify the model, making a proximal evaluation of each variant easier (and quicker!). For instance, if there are too many variables to be taken into account, let us omit some of them; if the dependence is nonlinear, let us approximate it by its linear proxy; if the process is random, let us use its momentums only; etc.

The distinguishing feature of this type of complexity, – i.e. whether the system is complex ("large") or simple ("small"), – is accessibility of modeling resources that are necessary for timely decision-making.

2.2. A complexity resulted from flaws in a model of structure

The characteristic ("*emergent")* property of a system is defined by the peculiar features of its *structure.* This is explicitly evident in analyzing *archetypes* of systems behavior (*Senge et al.,1994*): specific variants of a system's dynamic behavior ("*archetypes*") are produced by interactions between enforcing and balancing feedback loops inside the system structure. A model of a system's structure is a network of connections between parts of the system, which is a concerted union of black box models of all parts. And the danger of meeting unexpected difficulties when working with a real system stems from a possibility of creeping errors into the black box models of parts of the system. As is known, the four kinds of errors may happen in the process of building each black box model; and the probability of appearing a mistake in the model of a structure grows with the number of parts. Thus, chances of avoiding complexities of this type are based on our taking measures against making errors in modeling inputs and outputs of each part of the system.

2.2. A complexity emerged from the lack of information in a total model of a system construction

The working model of a system may be a combination of its models of parts and of structure (ties between parts). If the working model contains not enough information needed for achieving the goal, then the system becomes "complex". Here again this term has a new, special and relative meaning: it signifies not an attribute of a system but a relationship between the system and the person trying to manage it; this is *complexity due to ignorance.* The very same system may be "complex" for one person, and "simple" for another one: it simply means that they use models of different adequacy in designing their decisions about the same system.

Since the cause of such type of complexity is the lack of needed information about the considered system, it is obvious how to tackle this difficulty: one needs to mine the missing information from any possible sources and add it to a model. But in many cases this information about the system may be obtained only from the system itself. This means experimentation with the system: each trial is a question to a system "what are you?" (actually, "will you produce on your output the predicted on a model desired response to my input influence?"), and its reaction to your input is its answer. This information must be taken into account in all following actions with the system. Hence, the algorithm for managing that type of complex system is simple: it is sufficient to add into the previous model the knowledge received on each iterative cycle of interaction with the system. This algorithm is called a "trials-and-errors" one.

Every next cycle of this algorithm adds a portion of useful information to the working model of a system, thus making the model more adequate and the system less complex (more simple). This complexity of some systems is exhaustible: after a finite number of algorithm iterations, the system becomes simple (like the complexity of opening a cipher lock by trying all possible combinations one by one). But some systems are so complex that they never can be made simple (like Nature, economy, the human brain, etc.). So, the "complexity of ignorance" of a problem situation can be measured by the number of trials-and-errors needed to arrive to the acceptable solution for a problem.

3. A CLASSIFICATION OF COMPLEXITIES CONNECTED WITH THE TYPE OF SYSTEM'S UNCERTAINTY

3.1. Uncertainty of randomness

Going over from *static* models to *dynamic* ones demands the introduction of a new class of complexity, – that of control over *random processes*. Note the difference between probabilistic and chaotic systems: tackling the latter one is reduced to "dancing" with it, in attempts to recognize a *pattern* in ongoing events and adapt to it, trying making a match with it in one's own interests. In the probabilistic case, on the contrary, a possibility exists of using not only information about the observed unique realization but of using also the more general information about the entire ensemble of all realizations of the random process. Such general information is condensed in the function describing distribution of probabilities over the whole set of realizations of a random event or a process, under some additional conditions, like that of *stationarity* (statistical stability of the distribution in time) and *ergodicity* (statistical similarity of all realizations) of the process.

The complexity of work with a random phenomenon is caused by the uncertainty of predicting its behavior. But some characteristics of the distribution function may be estimated, monitored, and sometimes controlled, such as parameters of location and/or scale, correlation and regression, or, as suggested by C. Shannon, a measure of distribution uncertainty,– the entropy (*Shannon,1949*). This knowledge of the random process may be used in managing it, because the *measure of possibility* to obtain a certain result by intended intervention into a stream of random events (the *probability* of obtaining the desired result) depends on a number of conditions; and among them there is the subjective component of probability, – the level of cognition of objective conditions. (The spectacular examples of controlling social random events with the help of knowledge are lies, deception, cheating, scam, and fraud.)

Different levels of knowing a probability distribution function dictate using different methods for the extraction of required information from the same data sample. Correspondingly, mathematical statistics (theory of effective mining and processing of experimental data) has three branches:

1) Classical (parametric) statistics, based on the assumption that the distribution function is fully *known* (up to a finite number of parameters);

2) Non-parametric statistics, which assumes that observations are coming from the existing but *unknown* distribution function; and

3) Robust statistics, dealing with the cases when the probability distribution function is *known approximately*: when the real function lies in a vicinity of the given function.

In managing the random system, the proper methods (appropriate to your level of *a' priori* information) must be used for tackling the complexity.

3.2. A complexity connected with the "fuzzy" uncertainty

Uncertainty (which is a cause of a complexity) may be not only probabilistic. Very often several workers have to perform a certain job collectively. This means that each of them has his/her own model of the situation they are working on, but for the group work to be coherent, their individual models must contain enough of the same information in common, even in the case of *verbal* models. (The Bible describes the failure of the collective building of the Tower of Babel only because of mismatch, inconsistency of the builders' languages.)

If the common working language is a *professional* one (i.e. it provides sufficiently compatible meanings of phrases to all participants, like the languages of mathematics or engineering or medicine), then there is no difficulty (complexity) in communications. But when (as it often happens in governance) they work using informal colloquial language, the semantic ambiguity of words expressing qualitative estimations, evaluations, and gradations create difficulties in mutual understanding. The meaning of these words is diffuse, uncertain, vaguely expressed in a 'weak' qualitative (nominal or ordinal) measuring scale, and merely due to that, when different persons use the same grading term for the same evaluated item, they bear in mind quite different meanings. Perhaps all misunderstandings, disagreements and conflicts descend from these uncertainties in sense of words of the natural language.

Mathematical tools for the description of such complexity were developed by L. Zadeh (*Zadeh, 1968, 1996*). He suggested considering the words of uncertain meaning as a "*linguistic variables*" with their values belonging to a *fuzzy set.* Each grading word is the label of a fuzzy class. The polysemantic character of the linguistic variable means that a person believes that a *qualitatively* described entity x belongs to the given class with the certain (*quantitative!*) degree of confidence. This degree may take values between *0* ("certainly does not belong to") and *1* ("certainly belongs to") and represents the value of the *membership function* μ of belonging x to the named class: $0 \leq \mu_{class}(x) \leq 1$. Due to fuzziness, x may belong to several classes simultaneously – with corresponding degrees of confidence (with their sum equal to 1).

For example, a set of all pure numbers may be divided into three fuzzy classes: "small", "medium", and "large" numbers. And the two people would give overlapping but distinct membership functions of belonging to these classes. If they are working together, decisions about their joint efforts must be made by taking into account both opinions. For such needs certain operations were defined for certain combinations of given membership functions. For instance, for logical disjunction ("or", $\bigcup$), $\mu^{1\bigcup 2}_{class}(x) = \max [\mu^{1}_{class}(x), \mu^{2}_{class}(x)]$; for the conjunction ("and", $\bigcap$) it is defined as $\mu^{1\bigcap 2}_{class}(x) = \min [\mu^{1}_{class}(x), \mu^{2}_{class}(x)]$, etc. A fuzzy logic allows the compiling common managerial decisions from differing individual fuzzy judgments. It is a tool for coping with specific subjective complexity.

CONCLUSION

In conclusion, it should not be forgotten that classifications are (as are all models) mapping a reality just from a chosen particular point of view and approximately (with a satisfactory finite accuracy). The reality always differs from our perception of it. This is why complexities laying in wait for a man interacting with reality may disagree with indications of any class from our classifications.

Sometimes a concrete difficulty is a joint effect of several types of complexity. (For example, probabilistic uncertainty may be combined with a fuzzy one (*Zadeh, 1968*), or the objective and subjective uncertainties manifest themselves simultaneously (*Tarasenko, 1976*). In such cases one usually tries to construct a hybrid algorithm of those specific to particular types of complexity; and this is not an easy task.

However, real-life practice possesses often such a kind of complexity that is not covered by our formalized models. In systems thinking language those problems received the names "soft", "chaotic", and "wicked". Although some of their sub-problems may be formalized (for instance, by methods of *operations research*), for some others the certain heuristic ways of treatment are suggested (*soft methodology, brainstorming, synectics, project thinking, leverage points, pattern recognition, seven hats, foresight, etc.*); nevertheless their full solution lies beyond rationality. A conscious usage of unconscious resources of our brain (the subconsciousness, intuition, abduction) appeared recently in managerial science and practice (e.g., *Jackson,2009; Gladwell,2005; Stewart,2002; Bloom,2010*). In attempts to satisfy the requirements of Ashby's law of requisite variety, we are trying to confront complexity of our brain to the complexity of Nature. In one respect this is already achieved: calculations show that the number of possible combinations of states of all neurons in a brain is larger than the number of elementary particles in the Universe. But it is unknown how strong brain capacity is in sorting out these combinations.

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