ON DIFFERENT TREATMENTS FOR DIFFERENT TYPES OF SYSTEM COMPLEXITY

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Abstract. *A systems view of the world is currently the dominant paradigm in modern human practice. And in all practical cases 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 with 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 that the "professional" languages emerge. Look, for instance, at various meanings of the word "field" in agriculture, physics, surgery, geology, military, sports, and sociology.

The terms complex and complexity are no exceptions. Their variety of meanings in professional languages is now the hot theme in systems thinking research and discussions; a survey of them that is rich in content is given in Mohr and Gibbs (2014), Cabrera (2015), Worsley (2016).

A system is usually called complex 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 (governance). However, since the difficulties may have various causes, the different types of complexity must be distinguished. It is important to differentiate between them explicitly and precisely, because systems of different complexity types require very different approaches to tackling them. For this reason, systems with different origins of complexity even deserve to be named differently, not just called complex. An attempt to survey certain classifications of types of complexity and corresponding methods of treating them is presented in the following.

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

Studies of the dynamic behavior of systems described by fully deterministic differential equations of the second order partial derivatives have revealed a discreteness of types of their behavior: their trajectories in phase space tend to converge into one of four possible configurations (“attractors”) consisting of points, cyclic, torus-like, and “strange” ones (see for example Hirsh, 2004). The discovery of randomness of trajectories inside a torus and strange attractors became a real sensation. This discovery, together with the fact of limitedness of the number of attractors, each with a different degree of randomness of trajectories in it, was the third great achievement of the twentieth century in the cognition of Nature (the first two were the 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), straight in the order of the growing complexity of dealing with them (and therefore 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 of neutralizing 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 a trial-and-error algorithm is appropriate (note the specific narrowed use of the term complex in the case of insufficient knowledge of a controlled system);

• if a discrepancy between the desired and observed trajectories of a system behavior is small and may be compensated by a change in the parameter of a single system, then the algorithm of regulation (adjustment) is applied;

• if the discrepancy is so large that it cannot be eliminated by the regulation algorithm, then algorithms of restructuring, reorganization, and *perestroika* are applied;

• if a previously planned purpose proved to be contradictory to laws of nature (i.e. not feasible objectively), then changing the purpose to a supposedly achievable one is sometimes suitable;

• if the system is large (i.e., there is a lack of time for finding the optimal decision “just in time” because of the large dimensions of the system that lead to delayed modeling) then various ways of speeding up the decision making are applicable (note again the specific sense of terms large and small, distinct from that in informal English); and

• 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 cannot 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 when caught in a storm, or pilots flying through turbulence, or surfers maneuvering along the steep slope of a wave. As Meadows (2008) put it, chaotic systems cannot 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 use of information about the objective laws of development of Nature, such as fractalness, transitions between archetypes, self-organization, pattern recognition, and others. However, Jackson, who discussed in detail ten systems approaches to problem solving, warns about the much higher complexity of social systems than that of physical chaotic systems, which stems from the structure of social systems containing not only objective factors but additional subjective ones: human conscience and free will, divergence between stakeholders' opinions, various proportions of empathy, tolerance, and hostility between them, the quality of communication, and others (Jackson, 2009). This requires managers to turn to a creative holism and to be very cautious in practical application of the results of 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 of three basic models—the black box model (list of essential inputs and outputs), the model of composition (list of essential parts), and the model of structure (list of essential connections between parts)—or which combination of them is used as a working model in the particular case depends on the end pursued. Unfortunately, any model constructed may contain errors and mistakes, and this would create difficulties, various 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 full information about all elements of a system is necessary for successfully solving a problem: a full list of all the components of the system is needed. However, there are systems consisting of a huge number of elements. Processing the whole amount of information becomes complicated if it must be completed in a limited period of time. This difficulty is called a "curse of dimension" or a "big data problem" in the informatics community; in management such systems are called large. Kolmogorov (2005) suggested measuring the complexity of a large system by the length of the computer program that describes the system completely. A real-life example of a large system case was the 3–4-year delay in calculating by the 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 main causes of the poor efficiency of the totally centralized governance of the Soviet economy.

Thus, the essential characteristic of this aspect of complexity is the contradiction between the demand to do whole job no 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 the time needed to model them all exceeds the critical time assigned for decision making. Such systems are called large.

This situation may be tackled in two ways. The first 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 these require expending extra resources, and if there is a shortage of resources we are forced to use the second method of managing large systems: speeding up the decision making by switching from the time-consuming full optimization to the rapid finding of a satisfactory, acceptable solution. A not-optimal but timely decision is better than one that is the best 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 example, 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.

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

2.2. Complexity resulting from flaws in a model of structure

The characteristic ("emergent") property of a system is defined by the particular 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, what exactly is a concerted conjunction of black box models of all parts. And the danger of meeting unexpected difficulties when working with a real system stems from the possibility of errors creeping into the black box models of parts of the system. As is known, the four types of errors may happen in the process of building each black box model; and the probability of a mistake appearing in the model of a structure grows with the number of parts. Thus, the chances of avoiding complexities of this type are based on our taking measures against making errors in modeling the inputs and outputs of each part of the system.

2.2. Complexity from lack of information in a total model of a system

The working model of a system may be a combination of the models of its parts with its structure (connections between parts). If the working model does not contain enough information to achieve 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: it simply means that they use models of different adequacy in designing their decisions about the same system.

Since the cause of this type of complexity is the lack of needed information about the 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 desired response to my input influence, predicted by a model?"), and its reaction to your input is its answer. This information must be taken into account in all subsequent 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 in each iterative cycle of interaction with the system. This algorithm is called a trial-and-error one.

Every 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, the economy, the human brain, and others). So, the ignorance complexity of a problem situation can be measured by the number of trials and errors needed to obtain an acceptable solution.

3. A CLASSIFICATION OF COMPLEXITIES BY THE TYPE OF UNCERTAINTY

3.1. Uncertainty of randomness

Going 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 is reduced to "dancing" with it, in attempts to recognize a pattern in ongoing events and adapt to it, trying to make 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 unique realization observed but also of using the more general information about the entire ensemble of all realizations from 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 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 intentional 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. (Spectacular examples of controlling random social events with the help of knowledge are lies, deception, cheating, scams, and fraud.)

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

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; and

4) semi-parametric statistics, which assumes that parametric form of the distribution function is known, but real values of parameters are random variables.

In managing the random system, the proper statistical methods (specific for each of four levels of *a priori* information) must be used for tackling the complexity.

3.2. Complexity connected with "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 or 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 the mismatch, the 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 often happens in governance) they work using informal colloquial language, the semantic ambiguity of words expressing qualitative estimations, evaluations, and gradations creates difficulties in mutual understanding. The meaning of these words is diffuse, uncertain, and vaguely expressed in a weak qualitative (nominal or ordinal) measurement scale; and merely due to that, when different persons use the same grading term for the same evaluated item, they have in mind quite different meanings. Perhaps all misunderstandings, disagreements, and conflicts are rooted in these uncertainties in the sense of words of the natural language.

Mathematical tools for the description of such complexity were developed by Zadeh (1968, 1996). He suggested considering the words of uncertain meaning as "linguistic variables", with their values belonging to a fuzzy set. Each grading word is the label of a fuzzy class. The poly-semantic 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 value of the *membership function* $\mu_{class}(x)$ characterizing belonging of 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 (and 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 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 example, for logical disjunction ("or", $\cup$), $\mu^{1\cup 2}{}_{class}(x) = \max[\mu^{1}{}_{class}(x), \mu^{2}{}_{class}(x)]$; for the conjunction ("and", $\cap$) it is defined as $\mu^{1\cap 2}{}_{class}(x) = \min[\mu^{1}{}_{class}(x), \mu^{2}{}_{class}(x)]$, etc. Fuzzy logic allows 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 only 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 lying in wait for a person 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 may 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 often possesses a type of complexity that is not covered by our formalized models. In systems thinking language, those problems were termed soft, chaotic, and wicked. Although some of their sub-problems may be formalized (for example, by methods of operations research), for some others certain heuristic approaches 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 use of the unconscious resources of our brain (the subconscious, intuition, abduction) has appeared recently in managerial science and practice (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 the complexity of Nature with the complexity of our brain. In one respect this is already achieved: calculations show that the number of possible combinations of states of all neurons in the 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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