Chapter 1
Principles of Modeling in Information Communication Systems and Networks

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ABSTRACT

The authors present in this entry chapter the basic rubrics of models, modeling, and simulation, an understanding of which is indispensible for the comprehension of subsequent chapters of this text on the all-important topic of modeling and simulation in Information Communication Systems and Networks (ICSN). A good example is the case of analyzing simulation results of traffic models as a tool for investigating network behavioral pattarns as it affects the transmitted content (Atayero, et al., 2013). The various classifications of models are discussed, for example classification based on the degree of semblance to the original object (i.e. isomorphism). Various fundamental terminologies without the knowledge of which the concepts and models and modeling cannot be properly understood are explained. Model stuctures are highlighted and discussed. The methodological basis of formalizing complex system structures is presented. The concept of componential approach to modeling is presented and the necessary stages of mathematical model formation are examined and explained. The chapter concludes with a presentation of the concept of simulation vis-à-vis information communication systems and networks.

FUNDAMENTALS OF MODELS AND MODELING

A model is essentially the *re*presentation of an object, system or concept in a form different from that in which it occurs naturally. A model may likewise be defined as a tool, which helps in the explanation, understanding or perfection of a system. Modeling can be described as the process of substituting a test object (the original) for its image, description, or substitute object known as a model and providing a behavior close to that of the original within certain reasonable limits of assumptions and uncertainties. Simulation is

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usually performed in order to gain knowledge of the properties of the original object by studying its model, rather than the object itself.

The use of models is justified in cases when they are simpler in comparison with the option of creating the original object, or when the original object is better left uncreated for whatever reason. In the words of D.K. Nordstrom (2012), "Models are one of the principal tools of modern science and engineering…" Scientists and engineers devote a lot of time to design, build, test, compare, and revise models (Frigg and Hartmann, 2009).

A model may be the exact replica of an object (*albeit* on a different scale and from a different material) or depict certain characteristic properties of the object in an abstract form; i.e. a representation of a real system or process (Konikow and Bredehoeft, 1992). A model is thus essentially an instrument for forecasting the effect of input signals on a given object, while *modeling* is a method of improving the reasoning efficiency and intuitive capacity of specialists.

All models are but simplified *re*presentations or abstractions of the real world. An *abstraction* contains within itself the major behavioral traits of an object, but not necessarily in the same form or as detailed as in the object. Usually a large portion of the real characteristics of the object of study is disregarded, while such peculiarities that idealize a real event version are chosen. As a result, most models are abstract in nature.

The degree of semblance of a model to its object is called *isomorphism.* Two conditions must necessarily be satisfied for a model to be considered *isomorphic* (or similar in form) to the original object:

1. Existence of exclusive correspondence between elements of the model and the modeled object;
2. Maintaining the exact relationships or interactions between these elements.

From the foregone, we see that a model is essentially a physical or abstract object, with properties similar to those of the original object under study in certain defined ways. The specification of models depends on the particular problem of study as well as the available resources. The general requirements for models are as listed below:

1. **Adequacy:** This refers to the level of accuracy in replicating the properties of the original object.
2. **Completeness:** The ability of the model to deliver to the receiver all necessary information about the original object.
3. **Flexibility:** The ability to playout different situations in the whole range of conditions and parameters.
4. The *complexity* of developing the model must agree with the existing time and software constraints.

According to Tedeschi (2006), the design of the tests for adequacy for a particular model should of necessity evaluate weaknesses to be addressed. He further contends that a combination of several statistical analyses vis-à-vis the original conceptual purpose of the model is essential for determining its adequacy.

Since modeling s the process of creating a replica of an object and the subsequent study of the object's properties through the created replica (a.k.a. model), entails two major stages:

1. Model design;
2. Model evaluation/validation and conclusion derivations.

Model validation is concerned with ascertaining that a model performance in satisfactorily accurate vis-a-vis model design objectives; it is all about building the model right (Balci, 1997). It is pertinent to note here that a uniform procedure for validation does not exist, and as such no model has ever been (or will ever be) fully validated (Greenberg et al., 1976).

At each level of modeling, different tasks are resolved using means and methods that differ in context. In practice, different modeling methods are adopted. Depending on the method of their realization, all models belong to one of two classes: *physical* or *mathematical*.

Mathematical modeling is generally considered as a means of investigating processes and events via their mathematical models.

A good majority of models are *homomorphic* i.e. similar in form though with different basal structures. In this case, the semblance between different groups of elements and the object is only superficial. Homomorphism in models is a result of simplification and abstraction. In the design of homomorphic models, the system is first subdivided into smaller parts to allow for ease of required analysis. To this end, it is necessary to identify parts that are independent of each other in first approximation.

This type of analysis is linked to *real system simplification process* (i.e. discarding unimportant components or adopting assumptions of simpler relationships). For example, it may be assumed that there is a linear relationship between a certain set of variables. In control, it is common practice to assume that processes are either deterministic or their behavior can be described using known probability distribution functions.

Sequel to the analysis of the parts of a system their synthesis is embarked upon, this must be done accurately taking into consideration all available interconnections.

As the basis of a successful modeling methodology must be a thorough test of the model. It is common practice to start with a simple model and move towards a more perfect form, that depicts difficult situations more accurately. There is direct interaction between model modification and the data analysis process.

The Modeling Process consists of the following steps:

1. Decomposition of overall system investigation task into a series of easier tasks;
2. Concise formulation of aims;
3. Search for analogy;
4. Consideration of special numerical examples related to current task;
5. Choice of specific symbolism;
6. Documentation of obvious relationships;
7. Expansion of derived model if it can be described mathematically, conversely it is further simplified.

Hence, the development of a model is not limited to a single basic version. New tasks constantly emerge with the aim of improving the degree of *isomorphism*.

MODEL CLASSIFICATIONS

There is a myriad of ways for classifying models. In this section, typical model groups that can serve as basis for classification are mentioned. In the context of information systems, *physical* and *information* environments can be distiguished. Each of these environments can in turn either be described by *physical* or *theoretical* models.

Physical models are often called *natural* since in appearance they remind one of the system under study. They can be either a scaled-down (e.g. model of the solar system) or scaled-up (e.g. model of the atom) version of the system i.e. they are *scalable models.* Hereafter, only theoretical models of information systems will be considered.

Theoretical models can be subdivided into *mathematical* and *graphical models*.

Mathematical Models (MM): This is a compendium of mathematical objects and the relationships between them, which adequately depict certain properties of the object. In this category are models that employ symbols for the description of processes (e.g. differential equations *et cetera*), as opposed to physical properties. Hence, a mathematical model is the simplification of a real situation and can be considered as the abstract, formal description of an object that can be studied mathematically.

Graphical Models (GM): These show the relationship between different quantitative characteristics and are capable of forecasting the change in a set of quantities as a result of changes in others. Depending on the character of the selected properties of an object, *MM* is subdivided into *functional* and *structural* models.

Functional models depict processes concerned with the functioning of the object. They are usually in the form of a system of equations.

Structural models can take the form of matrices, graphs, lists of vectors, *et cetera* and express the spatial orientation of objects. These models are usually employed in cases when structural synthesis tasks can be defined and resolved by abstracting physical processes contained in the object. They reflect the structural properties of studied object.

So-called *schematic models* can be used for obtaining static representation of the modeled system, i.e. models containing graphical representation of the system *modus operandi* (e.g. technological maps, diagrams, multifunctional operational diagrams and schematic diagrams).

Considering the method of obtaining functional *MM*, they are subdivided into *theoretical* and *formal* models. *Theoretical MM* are obtained by studying physical laws. Equation structure and model parameters have a definitive physical interpretation. *Formal MM* are obtained on the basis of the effect of the property of the modeled object on the external medium, i.e. the object is considered a cybernetic 'black box'.

The theoretical approach allows for obtaining more universal models representative of a wider range of change of eternal parameters, while the formal *MM* are more accurate relative to the parameters used for measurement.

Depending on the linearity or otherwise of equations, *MM* are classified as *linear* and *nonlinear.*

In the context of set of values of variables, *MM* can either be *continuous* or *discrete*.

MM can be either *stochastic* or *deterministic* when the criterion for classification is method of description.

Using the form of connection between output, internal and external parameters as classification criterion, *MM* can be *algorithmic* (as a system of equations); *analytic* (in the form of dependence of output parameters on internal and external parameters); and *numerical* (in the form of numerical sequences).

Using the consideration of presence of inertia of physical processes in the model as classification criterion, there are *dynamic MM* and *static MM*.

In general, the type of mathematical model depends not only on the nature of the real object, but also on those tasks, for the resolving of which it is being developed as well as the required accuracy of their resolution.

MODEL STRUCTURES

Knowledge of the structural elements making up a model is necessary before its design is embarked upon. Though mathematical and physical models can be very complex, as a rule the basis of their makeup is always simple.

The general model's structure may be presented in the form of a mathematical formula

$$E = f\left(X_i \ , Y_i\right) \qquad (1)$$

where E – result of systemic action*;* X_i – controllable variables and parameters*;* Y_i – uncontrollable variables and parameters*; f*n of dependence of X_i on Y_i that determines the magnitude of *E*.

In the case of dynamic systems (Figure 1) an established way of representing their models exists. A complex system functions in a given external medium, the properties and states of which are characterized at every moment in time by a set of parameters forming a vector z (*disturbance*).

The systemic state and properties at every moment *k* is characterized by a group of internal parameters that are subdivided into *state vector* x and *control vector* u.

Dynamic model as a rule contains the following:

1. Description of all possible system states;
2. Description of the system state transition law;

$$x_{k+1} = F\left(x_k, u, z_k\right) \quad (2)$$

where F – vector function.

The set of all possible states of a system is otherwise known as the *state space* of the system. The *state space* can be either continuous or discrete.

The system state transition law is also known as *transition function* or *transitions operator*.

In the general case, a model is a combination of the following:

- Components
- Parameters
- Functional dependences limitations
- Objective functions

Components are parts that under right connections form a system. Components are sometimes regarded as *elements* or *subsystems* of a system.

A *system* is defined as a group of objects joined by a certain form of regular external action or interaction for the purpose of executing a given task.

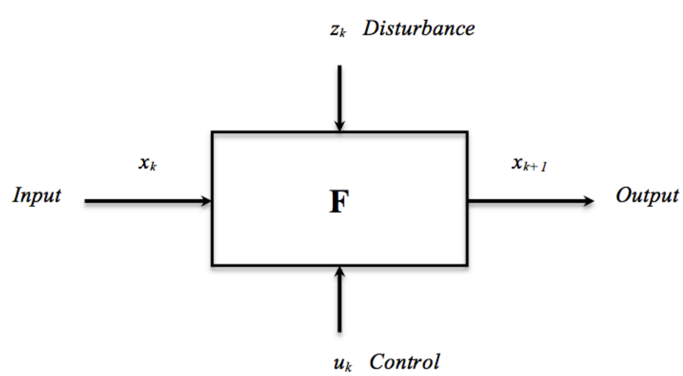
Parameters are quantities that may be selected arbitrarily unlike *variables,* that can only take values predetermined by the given function type. Once defined, parameters become constants.

In a model, there are *exogenic* (input) variables emanating from outside the system or resulting from external actions on the system as well as *endogenic* variables occurring in the system either as a result of internal interactions (state variables), or under the influence of output variables.

Functional dependences describe the behavior of variables and parameters. They express the following relationships between system components: *deterministic* – this is a definition that sets the relationship between given systemic parameters and variables in cases when the system output process is definitely known; *stochastic* relationships when given input information results in undefined results.

Limitations are a set range of change of value for variables or conditions limiting the spread of certain resources. They can be introduced by either the system designer (artificial limitations), or by the system itself as a result of its inherent properties (natural limitations).

Figure 1. Dynamic model of a system in "input – output" terms



Stage 4

This stage is for experimenting, testing, and correcting of the model under synthesis.

After a model has been developed, it is necessary to test its adequacy for the task it was created to perform. There exists a number of aspects of *adequacy evaluation*: the mathematical basis of the model must be non-contradictory and satisfy all laws of mathematical logic; the verity of a model is determined by its ability to adequately describe the starting situation.

Depending on the complexity of the mathematical description of a system, the following basic *ways of mathematical model usage* are identified: analytic research; qualitative research; research using numerical methods; simulation on digital computers (the opposite of analogue modeling).

Analytic Research

Presupposes the availability of a sufficiently complete and accurate analytical description of a whole system. As a rule, a mathematical model in its initial form is unsuitable for direct research (for example, it may not present required quantities in obvious enough form). In this case, it is necessary to transform the initial model *vis-à-vis* the input quantities in a manner that makes it possible to obtain results by analytic methods. This gives the possibility of obtaining sufficiently complete information on the functionality of the research objects. Suffice it to note here that practical application of this type of research is relatively rare.

Qualitative Research

This is embarked upon in cases when an obvious solution is absent, but certain *properties of the solution* can be found, e.g. *evaluation of solution robustness* etc. Investigation of the structural robustness of models using the relatively new methods of the mathematical theory of catastrophe falls under this category.

Numerical Methods-Based Research

This is employed sequel to the transformation of the model into a system of equations relative to input quantities. A solution is obtained by realizing a corresponding numerical method. However, problem solution is usually less complete in this case compared to the analytical scenario, since it doesn't show the structure and character of system functionality as a whole, but merely allows for the evaluation of its state at selected numerical values of the parameters.

The use of numerical methods has become very effective with the use of contemporary PC processing power. The use of PC however, is not the principal factor since all it does is limited to computational automation.

Expert opinion and *intuition* play a decisive role in the process of model formation (in the case of simulation). Expert opinion is engaged in choosing the most productive approach in resolving which elements to include in a model while it is under development.

SIMULATION

Shannon (1998) defines simulation as "the process of designing a model of a real system and conducting experiments with this model for the purpose of understanding the behavior of the system and/or evaluating various strategies for the operation of the system."

This is not limited to machine models alone. Results can also be obtained via paper, pen and desktop calculator. Imitation models are incapable of providing solutions in the form they are produced by analytical models. They only serve as a means of analyzing system behavior under conditions stipulated by the experimenter. For this reason, simulation is an experimental and application methodology, with an aim to describing the behavior of a system; develop theories and hypotheses, capable of explaining observed alize the formalization of each element and the relationship between them.

Depending on the character of system elements (deterministic, stochastic, continuous-time, discrete-time, etc.) typical mathematical schemes: differential equations, probabilistic automata, network switches, graphic models etc. employed for the description of elements.

Deterministic objects functioning in continuous time are usually described by differential equations.

Markov random processes or large-scale service systems are used to describe mathematical models of stochastic objects with continuous time. This method gives a false impression that all is taken into consideration. In reality however, the modeled object displays series of properties, which do not obtain from the set of properties of its elements.

Identification Method

Under this method, data collated by observing an object's input and output signals over limited time interval is used to create a mathematical model that optimally describes the studied object relative to given criteria.

If no conditions on the structure of the model are given *a priori*, then the task is one of *identification in the broad sense of the word.* A general method of solving this task does not exist at time of this writing. Under *identification in the narrow sense of the word*, an *a priori* form of the structure of certain mathematical model is added. In this case only the parameters of the adopted mathematical model need be defined.

STAGES OF MATHEMATICAL MODEL FORMATION

A generalized block diagram of the stages of forming a mathematical model is as shown in Figure 4.

Stage 1

Definition of model's objective function. Since a singular meaning for the term "*system model*" does not exist, it may be modeled in any way depending on the desired outcome. For this reason the elements of a model and their interactions should be selected based on the specifications of the task a system is required to perform. Using the example of a house, a builder sees it as the object of difficult tasks, while a sociologist sees it as just an element of the environment. Stage 1 delivers the most appropriate mathematical model, for example, with the use of block diagrams, employing system of equations and other mathematical methods.

Stage 2

At this stage, the block diagram of the discrete process is developed as well as *linking a system of equations to the discrete form*. This stage ends with the mathematical description and block diagram of all discrete systems.

Stage 3

At this stage it is imperative to *abide strictly by the time relationships* in the mathematical model being synthesized.

Figure 4. Block diagram of formation of a mathematical model

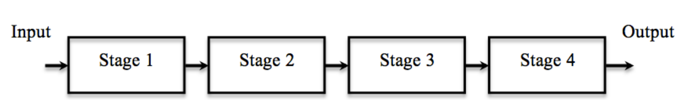
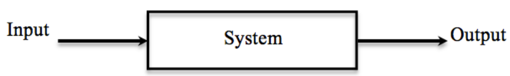


Figure 2. Model of a system



Control may be removed in the process of system development or on the basis of investigating similar systems.

Reverse task: This entails the use of system response and mathematical description of the system to determine the input signal. This belongs in the class of control tasks.

A more difficult task is one obtained if the input and output signals of a system are given and it is required to determine the mathematical description of the system. This is an *identification* or *system structural synthesis* task. The difficulty entails in the fact that one and the same state between the inputs and outputs of a system can be described by different mathematical expressions.

In the general case of component designation for converting input to output signals, there are three types of components (Figure 3):

1. **Conversion:** One or more input signals are converted into one or more output signals,
2. **Sorting:** One or more input signals are *distributed* (*sorted*) over two or more output signals,
3. **Feedback:** Input signals changes with a corresponding change in the output signal.

The difficulty level of system component structure is a function of the knowledge of the system *a priori*. If the nature of the process under investigation is known either partially or wholly, then the identification task is presented as <*black box*>. In this case, the system is described by means of linear or nonlinear equations with transfer characteristics. In certain cases it is possible to know a lot about the nature of a process and not know the values of only a few parameters, such an identification task is known as <*gray box*>.

The basic methods of developing mathematical models are: *axiomatic method*, *element equating method,* and *identification method.*

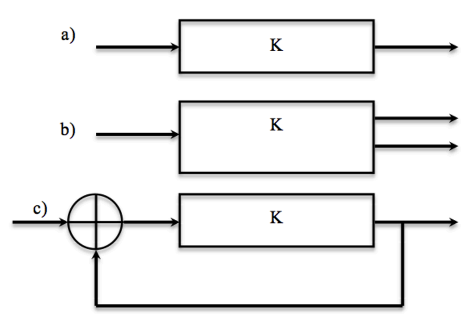
Axiomatic Method

This entails the *ab initio* postulation (formulation) of certain submissions relative to the real process expressed in the form of a set of mathematical expressions – *axioms*. Subsequently, definitive conclusions are made based on the axioms. The advantage of this method is that it allows for non-contradictory deductions in relation to the existing properties of the object within the limits of the adopted axioms. A major disadvantage of this method is the fact that the axioms are not tested in the course of the experiment.

Element Equating Method

A method used when it is required to develop the mathematical model of an object based on the properties of its components or when given a group of elements and it is required to develop a complex object and determine its properties. As a rule, complex objects are disintegrated into subsystems and elements so as to be able to re-

Figure 3. Types of system components: a) conversion, b) sorting, and c) feedback



velopment of formalized schematics is carried out in conjunction with specialists in the applied area of technology and modeling (or mathematicians). Though the form of description may remain textual, it must be a formal description of the process.

In order to develop formalized schematics it is imperative to select process characteristics; setup a system of parameters defining the process; define all interrelations between characteristics and parameters, while taking into consideration factors considered during formalization. In addition, a concise mathematical formulation of the research objective must be stated.

In the process of developing a model it is necessary:

1. To identify factors influencing the flow or the results of the process under study,
2. To select those that are susceptible to formalized representation (i.e. those that can be expressed quantitatively),
3. To group identified factors by common indicators, thus reducing their list,
4. To define quantitative relationships among them.

Usually, the most difficult stage of the modeling process is the translation of identified germane factors to mathematical language and the defining the relationships between these quantities. The crux of the matter lies in the contradiction inherent in the requirement for a componential and deductive model. In order to satisfy the componential requirement it becomes necessary to consider in the model as many real process factors as possible. The model naturally becomes more complex, leading to difficulty of its study and consequently obtaining componential results. However, the desire to obtain results through simpler methods invariably leads to a need for model simplification, hence reducing its componential nature. Reaching a sensible compromise is important; such that will guarantee neutral results and at the same time maintain the substance of the real process. To this end, an accurate set of all input data, known parameters and starting conditions is employed.

Componential description may not give all the necessary information for the development of formalized schematics, in which case additional experiments and observations of the process under study become necessary. In this case however, obtained results must be used completely in the development of formalized schematics.

Subsequent transformation of formalized schematics into a model is carried out without the input of any additional information.

In mathematical modeling, for the transformation of formalized schematics to mathematical model it is necessary to present in analytical form all relationships yet to be presented, express conditions as a system of inequalities, as well as give analytical form to other contents of the formalized schematics (e.g. numerical characteristics in the form of tables and graphs).

Numerical material is usually used in the form of approximating expression in Personal Computers (PC). Probability Flux Density (*pfd*) of typical probability distribution laws is selected as values for random quantities.

COMPONENT MODELING

Consider a simple system consisting of three basic objects (Figure 2): *input;* the *system;* and the *response (output)*. In order to model the system, two of these three objects must be known (given).

In the process of modeling individual components (elements, subsystems) of a complex system, different kinds of tasks are encountered. These can be divided into direct and reverse tasks.

Direct task: with the control describing a system as given, the response on an input signal can be determined. This task can be easily modeled.

Objective function (criterion function) is an outline of systemic aims and objectives and the necessary rules for measuring their achievement. Aims can be divided into *preservation aims* directed towards the preservation or sustenance of certain resources (energy) or states (safety), and *acquisition aims* connected with the acquisition of new resources or attainment of a defined state, to which the leader aspires.

The most general requirements on a model can be formulated as follows: a model must be *simple* and *understandable* to the user; *aims-oriented*, *reliable* i.e. guaranteed against production of absurd outputs; *user friendly; complete* from the view point of meeting main objective; *adaptive*, allowing for easy transition to other modifications or data reset; *allowing for incremental change*, i.e. starting out as simple, the model should have inherent capacity to become incrementally complex as a result of user interaction.

METHODOLOGICAL BASIS OF FORMALIZING COMPLEX SYSTEMS STRUCTURES

Any model of a real system is an abstract formally described object. A model describing the formalized process of a system's operation is able to encompass only its main characteristic *operational laws*, neglecting unimportant secondary factors.

The formalization of any real process precedes a study of the structures making up its occurrence, as a result of which a componential description of the process is obtained.

Component Description

This is the first attempt at a concise expression of the operational laws characteristic of the process under study and definition of the objective. It provides information on: 1) the physical nature and quantitative characteristics of elementary occurrences of the process, 2) the character of interconnections among them, 3) the position of each occurrence in the process as a whole. Component description can be written only after a detailed study of the process.

In addition to the description of the process proper the aims of modeling the process under study are also included in the componential description, which should contain a list of input quantities and their required accuracy respectively. This part of the formalization process can be executed without the input of mathematicians or corresponding specialist in modeling.

In this case, while creating the static representation of a system the following indicators of the existence of subsystems are analyzed:

1. Which components are to be included in the model,
2. Which elements will be excluded or considered part of the surrounding environment,
3. Which structural interconnections will be setup between them.

The definition of objectives should contain an exact description of the main idea of the proposed study, list of interrelations to be evaluated from the result of modeling, and stipulate those factors that must be considered in the design of the model. Data necessary for research are also included here: numerical values of known characteristics and parameters of the process (as tables, graphs), as well as values for initial conditions.

Componential description enables the construction of *formalized schematics* and *process models*.

Formalized schematics of a process is developed in cases when due to difficulty of the process or formalization of some of its elements a direct transition from componential description to models is either impossible or unjustified. Desystemic behavior; engage the theories in the prognosis of future systemic behavior.

Simulation is one of the few methods at the disposal of a researcher for solving problems. Since the choice of method must be tailored towards the solution of a problem, the question of when it is useful to employ simulation arises. Simulation can be employed if one of the following conditions is present:

1. A complete mathematical description of the problem does not exist (e.g. models of large-scale service system with queue consideration).
2. Complex and difficult analytical methods exist, but simulation gives a simpler solution.
3. Analytical solution exists, but they cannot be realized due to the low expertise level of available personnel. In this case, the cost implication of working with an imitation model is weighed against that of inviting a specialist.
4. In addition to evaluating certain parameters, there is the need to observe the process flow within a given period.
5. Simulation maybe the only possible option as a result of the difficulty of experimental setup and observing the process under real conditions (e.g. observing the behavior of space ships).
6. It may be necessary to record time scale (both slowing down and accelerating).

Advantages of simulation are: possibility of use in education and professional training; possibility of playing out scenarios of real processes in situations that help the researcher understand as well as have a feel of the problem leading to innovative ideas.

As a result, simulation is widely used, accounting for about 30% of all employed methods. This is irrespective of the fact that people with high level of mathematical training consider the imitation approach rough or the last means to be considered.

Imitation computation has a host of difficulties that boil down to the following:

- Development of a good imitation model is often expensive and time consuming, requiring the input of highly qualified specialists;
- Simulation is not accurate and its level of accuracy is not easily measurable. This can be resolved in part by analyzing the model's sensitivity to changes in certain parameters;
- Simulation in reality does not depict the real situation of things and this must be noted;
- The result of simulation is usually numerical, and its accuracy is a function of the number decimal places.

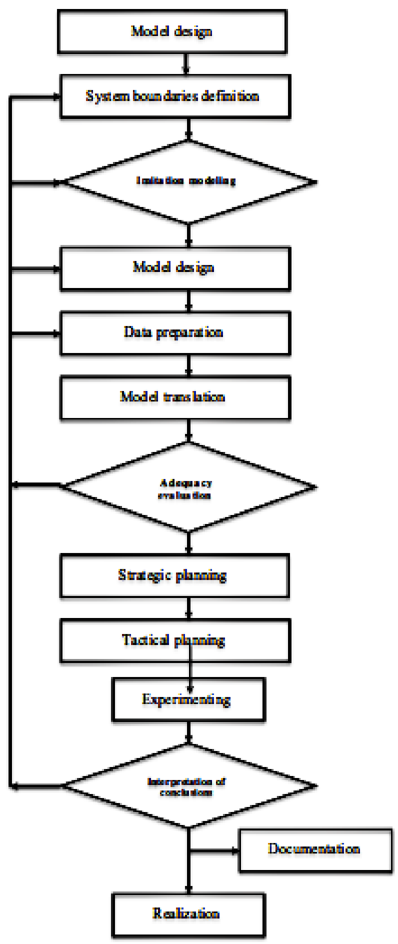
If it is possible to reduce a task (problem) to a simple model and solved analytically, then there should be no need for imitation since it is a last resort option. Besides, with each increase in available information on the problem at hand, the choice of employing imitation should be reassessed.

Imitation requires the use of powerful computers and a large set of data, which accounts for the high cost of this type of modeling in comparison with analytic models. The imitation process is as shown in Figure 5.

Since imitation is used for investigating real systems, the following stages of this process may be identified:

1. **System definition:** Boundary definition, limitations and evaluators of efficiency of system under investigation;
2. **Model formation:** Transition from real system to logical schematics (abstraction);
3. **Preparation of data:** Selection of data necessary for development of model, and their representation in the appropriate form;
4. **Model translation:** Description of model in a language acceptable for computer usage;

Figure 5. Flowchart of imitation modeling



5. **Evaluation of adequacy:** Raising certainty to acceptable level, at which a judgment may be made about the accuracy of conclusions about the real system;
6. **Strategic planning:** Planning of the experiment that should generate necessary information;
7. **Tactical planning:** Definition of method of executing each series of experiments, as contained in the experiment plan;
8. **Experimenting:** Process of executing imitation with a view to obtaining desired results (data);
9. **Interpretation:** Deduction of conclusions based on data generated from imitation;
10. **Realization:** Practical use of model and modeling results;
11. **Documentation:** Registration of project execution steps and its results, as well as recording of process development and usage.

For qualitative evaluation of a complex system, it is desirable to employ random process theory results. Experience of monitoring objects shows that they operate under the influence of a large quantity of random factors; this is why predicting the behavior of a complex system makes sense only within the limits of the probabilistic category.

In the study of the process of operation of each complex system considering random factors, it is necessary to have an exact understanding of the sources of the random interactions as well as reliable data on their quantitative characteristics. This is the reason for experimental collation of statistical material characterizing the behavior of independent elements as well as the system as a whole in real conditions, at the onset of any calculation or theoretical analysis in connection with investigating complex systems.

The main sources of random interaction are external factors and deviations from normal operating regimes (errors, noise, etc.) occurring within the system.

From the foregone, it becomes obvious that in the investigating of complex systems, consideration of random factors must be given utmost priority.

The effect of random factors on process flow is imitated with the aid of random numbers with predefined probability characteristics. Even then, the results obtained from a single modeling process should be considered as only the realization of a random process. Each of such realizations in isolation cannot serve as an objective characteristic of the system under study. Initial quantities are usually defined from averages and statistical processing of data from a large number of realizations, hence the common name of *statistical modeling method* for this approach. However, simulation can also be employed in deterministic cases, there are no statistical tasks whatsoever.

Statistical modeling method allows for the computing of the value of any functional element defined for the set of realizations of the process under study. For example, given the possibility of determining the value of efficiency indicator of a system by means of statistical experiments, a host of complex system analysis tasks become solvable, tasks such as: evaluation of effect of parameter (or initial value) changes on system efficiency; evaluation of the efficiency of various control principles.

Modeling results are also useful in system synthesis for the evaluation of various modes of its structure as well as perspective planning.

The statistical modeling method has a disadvantage inherent in any numerical method. Results obtained by this method evaluate system efficiency only in those situation for which modeling was done.

This serious disadvantage notwithstanding, simulation is currently the most effective method of investigating complex systems. At times, it is the only practically available means of obtaining information of interest on system behavior (especially during its development and modernization).

ANALYTIC MODELS (AM)

Presuppose the availability of mathematical description of processes, flowing in the original. They are usually developed under strict limitations on the parameters of the original and eternal medium. AM allow for obtaining relationships of the form:

$$P_i = f\left(\alpha_1 ,\ldots,\alpha_j\right) \qquad (3)$$

IMITATION MODELS (IM)

These are the most universal and can be developed in the absence of a mathematical model of the original. The simulation idea is a simple one; it entails the development of an algorithm of the behavior of subsystems and individual elements of the system in time. During the productivity analysis, only the state of the subsystem is of interest (functional or not). The algorithm may be realized in the form of a computer program. By repeating the execution of the IM algorithm in the presence of random events at the system input and within the system statistical information on the dynamics of change of important variables of the IM states can be collated. The statistical processing of this information allows for obtaining the statistical indicator of efficiency. Unlike AM, IM exhibits a strong medical error, depending to a large extent on sample size and consequently, on IM observation time.

CONCLUSION

The role played by mathematical modeling depends on a number of factors, including but not limited to: the character of task at hand, level of expertise of the investigator, amount of time and resources available for research, as well as the choice of model. It is important to always keep the original task in view all through the process of modeling.

The most common error is related to the fact that investigators often lose track of the original task and main aim. The other and not less important mistake stems from moving on to the modling stage without sufficient data on the systems past behavior.

A systematic method comprising of the following stages is available in the literature:

1. Problem statement,
2. Aggregation of experimental data,
3. Determination of the effect of system's working paramenters,
4. Setting up of experimental methodology (e.g. changing of parameters with a view to determining factual effect on observed results),
5. Reducing the number of working parameters (by eliminating those parameters to which the system is least sensitive),
6. Determination of method's characteristic limitations.

One of the major mistakes usually committed by researchers during modeling is the perceived notion of a need to try and change real conditions, i.e. the conditions observed in real-world or technical systems. This perceived need often arises in their bid to employ specific models that were developed for other purposes. Such an approach is definitely not sensible even if it appears to be justifiable.

The researcher's task is not limited to just model development. Upon a successful development of the model, it is imperative to populate it with necessary information, in order to determine how accurately it mimicks the modelled system by a comparison with previously obtained experimental empirical data. In conclusion, the onus rests on scientists and engineers to always keep in mind that perhaps the simplest and most concise definition of a model is – A model is a simplification of reality (National Research Council, 2007).

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