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SYSTEM DYNAMICS MODELS IN MANAGEMENT PROBLEMS SOLVING

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The models represent the key methodological tool for management problems solving in System Dynamics (SD) as a functionalist systems methodology. Above all, it is about mathematical models, built according to appropriate feedback structures, i.e. specific elements and flows that form feedback loops. Since SD is based on the assumption that a system structure represents the behavioral key determinant, SD models provide an effective prediction of the future system behavior. The paper focuses on the modeling process in SD, as a complex, iterative process, consisting of the following phases: model conceptualization, formulation, testing and implementation. Although being extremely useful in solving numerous organizational managing problems, SD models have certain disadvantages as a consequence of their quantitative nature. Qualitative modeling and group model-building, as possible directions for further SD development, are appropriately important in SD models` deficiencies elimination.

Keywords: System Dynamics, modeling process, System Dynamics models, management problems solving

JEL Classification: M10

INTRODUCTION

Different systems approaches and methodologies can be applied in researching and solving contemporary management problems. System Dynamics (SD), as a relevant systems methodology, is appropriate for management problem situations characterized as complex and unitary. According to this, and bearing in mind the SD key determination – focused on researching the feedback structure generating a certain system behavior – SD represents relevant structuralist-functionalist systems approach to management. The basic allegations of the management problem situations in SD are the structure and processes within SD, and the key tools in management problems solving are appropriately developed models. In that sense, the research will be focused on the SD modeling process, i.e. SD models as relevant tools for management problems solving within contemporary organizations.

The aim of the paper is to demonstrate SD possibilities, i.e. its models, in dealing and solving contemporary management problems. In fact, the aim is to demonstrate the ways in which SD can help managers move through adequate problem areas in predicting a future behavior and designing certain policies for an improvement in organizational functioning.

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This paper is based on the following key hypothesis: If the structure represents the key determinant of a system behavior, then SD models – through appropriate computer stimulations – provide a prediction of a future behavior for the researched system.

First of all, the paper introduces the key SD features as a functionalist systems approach to management. Then, the process of SD modeling is researched, i.e. certain characteristics and modeling process phases are specified. Since the focus is on the modeling process itself, each phase is considered separately – conceptualization, formulation, testing and implementation. The SD model is briefly illustrated in the paper on an example of a new product adoption on the market, because this is about tools with an exceptional applicative potential. Finally, some deficiencies of SD models are identified, as well as possible directions for further SD development through qualitative modeling and group model-building.

SYSTEM DYNAMICS – A FUNCTIONALIST SYSTEMS APPROACH TO MANAGEMENT

System Dynamics, as a systems approach to management problems solving, is based on the theory of information feedback and control. SD focus is on the problems that can be modeled as systems, essentially made of different elements and flows, i.e. inter-elementary relations that create a feedback loop and are represented as continual processes. Appropriate deterministic model structures not evolving over time are developed for those systems. SD modeling and simulation are widely used in the field of social, and especially economic, systems and different types of organizations, with a significant stress on the policy and design analysis.

J. W. Forrester (1972) made foundations of SD, originally entitled as Industrial Dynamics. SD deals with time changeable interactions of different parts of the management system in order to determine in which way the organizational structure, policy, time delay in making decisions and actions interact affecting the system`s success.

Since management problem situations are represented by a appropriate structures and processes within, the theoretical base of SD is as follows (Petrović, 2010, 369): A system`s behavior is primarily conditioned by its structure. It is supposed that the considered structure and processes can be represented by adequate diagrams and mathematical models of system. According to the SD theory, a lot of variables of the existing complex systems become casually connected in corresponding feedback loops. System connections between feedback loops constitute the system's structure, and that structure is the key determinant of the system`s behavior. (Jackson, 2003, 67).

As an essential SD aggregate, a structure is determined by (Petrović, 2010, 370-371): line, feedback direction, nonlinearity and loop multiplicity. The number of levels, i.e. number of variables used for representing the structure of the researched system, determines the system line. Feedback can be positive and negative, considering the direction. Positive feedback causes an increase, i.e. creates a rise or a fall, and the negative one means a specific preventing or controlling influence. The nonlinear connecting of positive and negative loops can lead to loop domination, allowing controlled growth. Management problem situations are, as a rule, represented by structures with multiple positive and negative loops. It is assumed that an effective prediction and control can be made and conducted, respectively, by specified structure characteristics. Time-based mathematic SD models simulate possible scenarios of an organization's functioning, and, in that way, provide relevant trends projections. Starting with the fact that a concrete prediction is reliable, the focus is accordingly transferred to introducing appropriate control policies.

Beside SD prediction and control, the SD model is of a great importance, and its basic aggregates are levels and rates. The level is considered to be a changeable value over time. In other words, levels are the present variable values, i.e. values that have resulted from an accumulated difference between inflows and outflows (Forrester, 1972, 68). Apart from levels, rates define the present flows among a system's levels. Rates correspond to an activity, while levels measure the resulting state which the system has been brought to by the activity. For example, the number of employees represents the level determined by the hire rate and the quit rate; or the debt level is determined by the borrowing rate and the repayment rate, etc. (Sterman, 2000, 200).

The mathematical expression of the SD model is represented by a system of equations (levels and rates equations) controlling variable interactions of the considered problem situation that change over time. Since the modeled system moves over time, from time to time it is necessary that equations be converted. Different pieces of software, such as: DYNAMO, Powerism, Venism, have been developed to support SD modeling and simulation.

THE MODELING PROCESS IN SYSTEM DYNAMICS

Modeling, as an integral part of the learning process in organizations, represents an iterative, continual process of the formulating, testing and revision of both formal and mental models. As an adequate expression of management problem situations, the models are a powerful tool for identifying and representing their key determinations, ways they are manifested and their relevant implications. According to that, valid models are an extremely useful methodological tool in organization management, i.e. in deciding on the way a manager should go through management problem areas in contemporary organizations (Petrović, 2010, 572). The aim of the SD model is to identify policies and organizational structures that improve functioning and provide an organizational success.

The modeling process should be focused on important questions, such as essential organizational problems, and is part of the organizational and social contexts. Before the modeling process starts, the modeler must have access to the organization and identify clients. That is about individuals and groups whose behavior is affected by the modeling process, i.e. whose behavior has to be changed in order to solve the problem. The modeling process should be consistent with clients' skills, abilities and aims. Most clients are interested in the fact that models should support conclusions already made, or use them as power tools inside the organization. However, the modeler must be prepared to inform clients about their wrong assumptions, if the modeling process says so (Sterman, 2000, 84-85).

The SD model should have the following characteristics, namely, it should be (Forrester, 1972, 67):

- able to describe any problem in cause-effect relations;
- mathematically expressed in a relatively simple way;
- able to include numerous variables, within practical computer ability limits;
- able to manage different discontinuities, not affecting the results, but generate discontinued changes in decisions when necessary.

SD modeling is a process carried out through several phases, and authors classify it in different ways.

Luna-Reyes & Andersen (2003, 275) specify the modeling process phases according to various authors. In that sense, there are following classifications: conceptualization, formulation, testing and implementation; then: problem definition, system conceptualization, model formulation, analysis of model behavior, policy analysis and model use; or: diagram constructing and analysis, simulation phase (stage 1) and simulation phase (stage 2).

Also, Sterman (2000, 86) classifies the modeling process phases into: problem articulation, dynamic hypothesis formulation, simulating model formulation, model testing and policy formulation and implementation.

In spite of different classifications of certain phases, generally, the modeling process includes the following activities (Jackson, 2003, 68-69): Above all, the conceptualization phase, clarifying the problem and identifying variables having an influence on it. Then, the feedback loop model revealing relations among variables is built. That model, in the formulating phase, further develops into an appropriate mathematical model, i.e. level and rate equations. Those equations, helped by a certain piece of software, provide a relevant computer simulation of a system behavior. The model validity is estimated in the testing phase, and possible ways for improving the results for the system functioning, i.e. certain policy designing, are identified in the implementation phase.

The aim of the conceptualization phase is to build a conceptual model representing a relevant problem within the system. It is necessary that the following activities be conducted in this phase (Albin, 1997, 6):

- the definition of the model purpose;
- the determination of the model boundaries and identification of its key variables;
- the description of the model behavior, i.e. building the reference mode of the key variables;
- the presentation of the system feedback loops by diagrams.

The most important step in the modeling process is problem defining, i.e. setting the model purpose. Each model is the representation of a certain system. In order to be useful, a model should deal with a specific problem and simplify rather than reflect the system in details. The system usefulness lies in the fact that they simplify reality by creating a representation of something that can be understood (Sterman, 2000, 89). The modeler should also consider who the model is primarily designed for. Reaching agreement on the model purpose is of an essential importance. It is very difficult to decide which system components are important without a clear and strictly defined purpose. If the purpose is defined too widely or too abstractly, the model will include too many components and will be too complex for any practical analysis.

The most common mistakes in defining the model purpose are (Albin, 1997, 9):

- the purpose does not enables system understanding;
- the purpose does not reveal policies to improve the system behavior;
- the purpose does not reflect mental models and is not used as a communication and unification tool.

After having chosen the problematic focus field, the modeler must collect relevant data and define the model. When talking about the model boundaries, it is necessary that the fact that every feedback system has closed boundaries which are a frame for generating a certain analyzed behavior be stated. Above all, the modeler has to explore all components considered to be necessary for the system model. It is about the initial components list. In order to specify the model boundaries furthermore, the modeler must divide the initial components list into two important groups (Albin, 1997, 10; Sterman, 2000, 97):

- endogenous – dynamic variables included in the feedback loops of the system, and
- exogenous – components whose values do not directly affect the system.

After dividing these two groups of components, it is necessary that we determine which components are stocks and which are flows. It should be marked that exogenous components can be neither stocks nor flows, but adequate constants (Albin, 1997, 11). The endogenous phenomenon explanation is something that is tended to within the SD, as well as that a problem should be described dynamically, i.e. as an appropriate kind of behavior, developed over time. The time interval should be determined in a way that it can include enough information about the past in order to show the reasons for the occurrence of the problem and describe its symptoms. Also, it should include relevant information about the future to include the delayed and indirect effects of potential policies. The most significant difficulty in mental models is a tendency to think of causes and effects as local and current. In dynamic, complex systems, the cause and effect are distant over time and space, which considers feedback systems to be the ones with long delays, distant from the decision point or the problem symptom (Sterman, 2000, 91).

The reference mode, i.e. a set of diagrams showing the way a problem occurs and how it can evolve in the future, is built after determining the model boundaries and time interval. The reference mode, in fact, represents the key variables behavior over time and can be useful before and after the model building. Reference modes can be changed during the modeling process, and, according to the initial reference mode, the modeler can reassess and redefine the model purpose.

The last step in the conceptualization phase represents the feedback system structure. SD uses different types of diagrams in representing feedback structures. Those are causal loop diagrams, stock and flow diagrams, structure diagrams and policy structure diagrams (Lane, 2008, 9). This paper briefly considers causal loop diagrams and stock and flow diagrams, as the most commonly used tools for the diagram-based representation of a system structure in SD.

Causal Loop Diagrams (CLD) show, above all, the orientation of feedback, as well as the key elements, i.e. variables, and their mutual interaction. Variables are connected by causal links, represented by adequate arrows. Relations that produce change in the same direction (rising or falling) are marked with a positive sign in the causal loop diagram. The positive feedback link means that if the cause increases, the effect also increases above what it would otherwise have been. Also, if the cause decreases, the effect decreases below what it would otherwise have been. Opposite to that, the negative feedback link means that if the cause increases, the effect decreases below what it would otherwise have been; and if the cause decreases, the effect increases above what it would otherwise have been (Sterman, 2000, 139).

Therefore, each link is characterized by a certain polarity, i.e. by the effect direction which the influencing variable has on the influenced variable (Lane, 2008, 5). This describes the structure of the system, not behavior of the variables. Also, this describes something that would happen if a change occurred, not something that really happens. The previously stated expression below or above what it would otherwise have been, has an important significance because an increase or a decrease in the causal variable does not necessarily mean the effect will actually increase or decrease. Beside determining the link polarity, it is necessary that loop polarity be determined. Since there are more possible positive and negative links, the loop polarity can be determined by multiplying the signs of the link polarities in a loop and finding the net sign (Lane, 2008, 10).

CLD have certain deficiencies, such as: a lack of precision, a lack of distinctions between stocks and flows, mistakes in determining the loop polarity, etc. (Lane, 2008, 12-14).

Stock and flow diagrams are more detailed than causal loop diagrams. Each causal loop has to contain at least one level. If a causal loop does not contain a level, the behavior over time that should be examined cannot be identified. Each element is represented adequately in stock and flow diagrams (Sterman, 2000, 192):

- stocks are represented by rectangles;
- inflows are represented by arrows that flow into" the stock;
- outflows are presented by arrows that "rise" from certain stock;
- valves represent flows;
- clouds represent the sources or sinks for the flows. The source represents the stock which the flow arises from, and sinks represent the stocks which the flows "flow into".

Some mistakes (such as determining the link and loop polarity) can be avoided by presenting feedback loops in stock and flow diagrams; therefore, relations among components in stock and flow diagrams are strictly defined, contrary to causal loop diagrams. Being generally more complex and more time demanding to create, stock and flow diagrams provide much more information than causal loop diagrams. According to that, they are an adequate base for making conclusions about the system behavior (Lane, 2000, 244). However, there are certain limits for their use: they can encourage excessive detailing; be too complex and technically oriented; cannot enable a diagram explanation for all types of phenomena, etc. (Lane, 2000, 244; Lane, 2008, 15).

According to causal loop diagrams and stock and flow diagrams, it is possible to determine a set of equations in the model formulation phase, i.e. develop an adequate mathematical model of the situation which is being researched. Due to the fact that time is one of the key factors, it is necessary to determine the successive series of the system's state over time, and consequently a periodically converted equation. According to Forrester (1972, 74), a series of calculations that should be done is presented in the Figure 1.

The basic equations of the SD model are divided into two groups: level equations and rate equations; however, level equations are calculated first (Petrović, 2010, 377-379): Level equations show the ways for determining levels in time K, based on the levels in time J and on rates over the interval JK. Level equations are independent of each other, and only depend on information before time K. That is why the level in time K depends on: the previous level value in time J and the rate in the time JK.

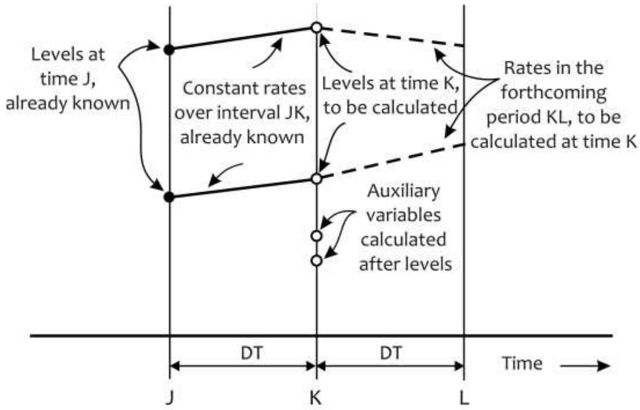

Figure 1 Calculations in time K

Source: Forrester, 1972, 74 (According to: Petrović, 2010, 378)

Rate equations are converted at the present time K, after level equations have been calculated. The values having been determined by rate equations determine the rates that represent actions which will be taken in the following KL time interval. Therefore, rate equations determine flows among the levels of the observed system. Rate equations are calculated according to the present level values in the system, and the starting level and the "flow-into" level are included as a rule. Rates cause level changes. Generally, rate equations should be observed as a control tool of what will happen within the system in the forthcoming period. However, certain auxiliary variables, as an appropriate subgroup, can appear within rate equations. Rate equations are independent one of another, and their mutual interaction is done through their future effects on the levels.

Time is indexed, i.e. moved to the right for one time interval, when the level is calculated for time K and rate for the KL interval, i. e. in Figure 1, levels in time K become levels in time J, and rates for interval KL, rates for the JK interval. This means that time K, representing the present, moves by one DT length interval. Then, a set of calculations can be repeated in order to determine a new state of the observed system in the time which is for one DT interval later than the time from the previous state. The developed model determines the movement of the system throughout time. Generally, a level, i. e. stock, can be presented by the following equation (Sterman, 2000, 194):

$$Stock(t) = \int_{t_0}^{t} \left[Inflows - Outflows \right] ds + Stock(t_0) \quad (1)$$

where stock is determined in time t (time K in Figure 1) and inflows are determined at any moment between the starting time t_0 and the current time t. The same way, the net flow of change of any stock, i.e. its derivative, represents a difference between the inflow and outflow, defining a certain differential equation:

$$d(Stock)/dt = Inflow(t) - Outflow(t) \quad (2)$$

Beside level and rate equations, the so-called auxiliary equations, i.e. equations decomposed from an appropriate level equation in a situation when a level equation is extremely complex, represent a separate class of equations in the model. Contrary to level and rate equations, auxiliary equations have to be calculated in a precisely determined order. In principle, auxiliary variable depends only on: already known levels and auxiliary variables that can be calculated.

Apart from the stated equations, equations for the starting values are significant. They define the initial values of all levels and some rates that have to be determined before the calculation of model equations starts; however, these equations are used to calculate the values of some constants. Converting the presented equations is done by computer, i.e. specially developed software used in SD. When the formulated model enters computer software, it is necessary that several preliminary simulation researches be done. It is necessary that an appropriate value of the DT interval be determined and the system state stability analyzed. (Petrović, 2010, 382-383):

When determining DT time interval, it is necessary that attention be paid to the relation between the stimulation speed and accuracy. Generally, the DT time interval is determined by the shortest time constant used in the model. The state stability analysis of the system gives information about the reliability of the model itself or the stability of the modeled reality segment.

Testing or the model validation is considered to be a comparison of the model to the reality in order to accept or reject the model. In fact, validation in SD is a process of establishing confidence in the model correctness and usefulness. This is about a complex process, where everybody has their own aims and criteria for the model validity. The idea of validity as an equivalent for confidence is in conflict with the understanding of validity equally as an absolute truth. Confidence in some model is an adequate criterion because there are no proofs for absolute correctness that a model represents reality. Validity is also relative in a sense that it can only be properly assessed for a particular purpose. According to that, validation cannot be a completely objective and formal process, but must have subjective and qualitative components. In other words, model validation is a gradual process of establishing confidence in models (Forrester & Senge, 1979, 8; Barlas, 1996, 188).

There are a great number of tests for model validity that can be classified in different ways. Forrester & Senge (1979) find following tests:

1. tests of model structure (parameter verification test, boundary-adequacy structure test, extreme-conditions test, etc.);
2. tests of model behavior (behavior-reproduction test, behavior prediction test, change-behavior test, etc.);
3. tests of policy implications (system-improvement tests, changed-behavior-prediction tests, policy-sensitivity tests, etc.).

Barlas (1996, 189) singles out the following validity model tests in SD: structure validity tests (direct structure tests and structure-oriented behavior tests) and behavior validity tests.

Since there are many tests, there is a question if all tests have to be used. Besides, it is important that the question when to end the model validation process be considered. In that sense, ending the model validation process depends on the following determinants: the costs of validation, a potential degree of model validity, the model size, clients` expectations and clients` experience with modeling, relative importance, i.e. risk of decision, data intensity and availability and the modeler`s level of expertise (Schwaninger & Groesser, 2012). In spite of the fact that it will not always be possible to use all the tests for establishing confidence in the SD models, a wide range of tests increase a probability for using a greater number of tests and including more people into the whole process of model validation. Thus, one of the key determinations of the previously mentioned tests is the easiness of implementation. The accessibility of the whole testing process is crucial for the probability of a modeling success in SD (Forrester & Senge, 1979, 36; Richardson, 1996, 147).

The last phase in the modeling process is the implementation phase, i.e. models application in policy designing. Once trust into the structure and model behavior has been established, the model is used for designing appropriate policies. Designing policies is much more than changing the parameters value, and includes creating completely new strategies, structures and decision rules. While the feedback system structure determines its dynamics, policies will include change of dominant feedback loops by the redesigning of stocks and flows structures; by eliminating the time delay; by change of flow and quality of information available at the key decision points; or by fundamental reformulating the decision-making process within the system (Sterman, 2000, 104). In fact, SD models can be used for redesigning: system structures and/or decision policies (Petrovic, 2010, 382). The model implementation does not end with the ending of a certain project or solving a certain problem, but can be applied for solving some other, similar problems (Sterman, 2000, 81).

ILLUSTRATION OF THE SYSTEM DYNAMICS MODEL APPLICATION

Let the object of the observation be a company that has introduced a new product to the market, with an to research the process and predict the dynamics of the adoption of the new product in the market. In that sense, an appropriate SD model providing the prediction of the dynamics of the adoption of a new product on the market can be developed. F. Bass (1969) gives preliminary assumptions of the models developed further within the SD conceptual framework (Morecroft, 2007; Sterman, 2000).

Figure 2 shows the model of a new product adoption and the identified key stocks, flows and feedback loops. This is the model inclusive of potential adopters, considering the word-of-mouth for the product only. The model, in which the adoption rate represents the result of the word-of-mouth, implies the two following assumptions (Bass, 1969): Above all, it is necessary that there be initial adopters, i.e. the value of this variable in the model must not be zero, which means that there must be one or more people who have already been using the product. Also, it is assumed that the product is bought only due to the information and recommendations of the current adopters. These kinds of assumptions limit the model generality, which can be prevented by advertising, an important determinant of a new product adoption on the market.

There are two key stocks (Sterman, 2000, 324-325): adopters and potential adopters, and the adoption rate is equal to adoption from the word-of-mouth. Also, there are two feedback loops – one, positive or reinforcing, represented by the word-of-mouth, and the other, negative or balancing, represented by market saturation. The positive loop shows that, if there are more adopters, there will be more people who can orally propagate the product. First, this loop dominates the system and generates growth. Contrary to that, the negative loop slows the system down, since the number of potential adopters decreases due to market saturation (because each new adopter originates from potential adopters). The aim is to eliminate potential adopters, i.e. make all potential adopters be transformed into product adopters.

It is assumed that the total population (a potential product market) is made up of a million people occasionally talking about their shopping. This tendency is marked by the contact rate and is assumed to be 100. The number of adopter contacts with the rest of the population per year represents the multiplication of the contacts rate and adopters. Some of these contacts lead to product adoption (while the contact of two adopters cannot generate a product adoption). A probability that any randomly selected contact, i.e. the one between an adopter and a potential adopter, is equal to the proportion of potential adopters in

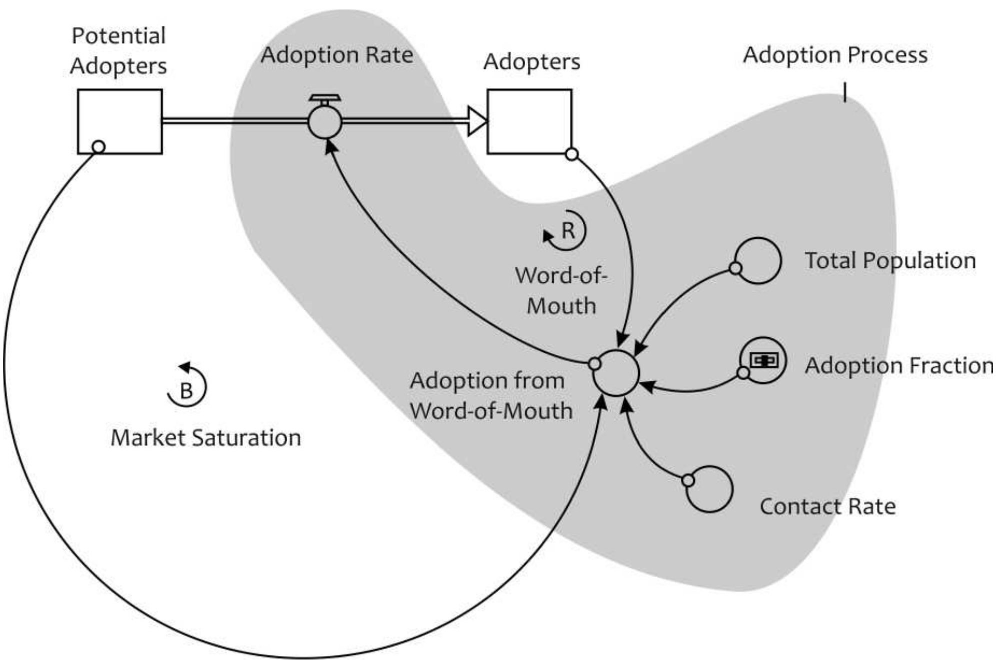

Figure 2 Key stocks, flows and feedback loops in the process of a new product adoption

Source: Morecroft, 2007, 167

the total population. This relation decreases if the process of adoption continues, and reaches zero, when the market is completely saturated. However, not all adopter contacts will result in product adoption. The fraction of successful contacts is called the adoption fraction, its assumed value is 0.02, which means that 2% of all contacts lead to product adoption. The contact rate and the adoption fraction determine the word-of-mouth.

Time is marked in years in the model, and dt represents a moment small enough to provide numeric accuracy. The number of adopters at a specific time equals the sum of the previous number of adopters and time (t-1) and the adoption rate over the interval dt. Contrary to that, the number of potential adopters at time t equals the subtraction of the previous number of adopters (i.e. the number of adopters for time t-dt) and the adoption rate over the interval. It is considered that, initially, there are 10 adopters among the total population of one million, so the rest are potential adopters. The adoption rate is equal to adoption from the word-of-mouth.

If the stated variables are marked like this:

A - adopters

AR - adoption rate

PA - potential adopters

IPA - initial potential adopters

AWM – adoption from word–of –mouth

CR - contact rate

AF - adoption fraction

TP - total population

then the following equations can be determined (Morecroft, 2007, 168- 169):

$$A = A(t - dt) + (AR) * dt \tag{3}$$

$$PA(t) = PA(t - dt) - (AR) * dt \tag{4}$$

$$IPA = TP - A \tag{5}$$

$$AR = AWM \tag{6}$$

$$AWM = CR * A * (PA/TP) * AF \tag{7}$$

The dynamics of product adoption by the word-of-mouth is shown in Figure 3, where initially there are only ten adopters who start transferring their own experiences, i.e. propagate a product. During the first five years, adopters and their followers very slightly influence the rest of potential adopters who have not heard of the product yet. According to that, in a certain period of time, the adoption rate is close to zero; however there is a relatively small growth compared to the total population of million people. During the fourth year, adopters begin to grow in number. Therefore, the largest number of the total population become product adopters in the time interval between the fifth and the eighth year from the product introduction to the market. After that, the adoption rate begins to fall, since market saturation grows.

If there were zero initial adopters, even with a million potential adopters, there would be no growth, since the product is not known. All the above stated demonstrates a need for the existence of initial adopters in order to start with the the word-of- mouth, which represents the key model assumption. It is necessary that more elements, such as product advertising, included in order to create a base of initial adopters. In that sense, this model can be expanded by introducing advertising and following their effects on product adoption (Morecroft, 2007, 171).

Since SD models can be applied to any dynamic system, there are a great number of case studies and examples of their successful use (Forrester, 1972; Sterman, 2000; Morecroft, 2007).

QUALITATIVE AND GROUP-MODEL BUILDING IN SYSTEM DYNAMICS

There are certain advantages in management problems solving in SD: SD's strength lies in an assumption that the structure is the key determinant of a system behavior and the structure can be represented by appropriate positive and negative feedback loops. The understanding of feedback structures can help managers to manage complexity better and provide more efficient decisions for achieving their goals. Since SD models pointing out the key decision points and actions of the ones who make those decisions are included in the models, the consequences of the current policies can be determined and alternative strategies can be researched (Jackson, 2003, 78).

However, critics consider SD models as imprecise, and not strict enough, i.e. those models are usually built on ignoring certain theories in the researched field or without a sufficient amount of collected data. If SD models are imprecise, then a precise prediction of the future system states can all but be provided, at the same time it will be just partially useful to decision-makers (Jackson, 2003, 79 – 80).

Richardson (1996), too, states the following problems as the key ones in a further SD development: understanding models behavior, model validity, the improvement of practical models application, models accessibility and availability, qualitative versus quantitative modeling, i. e. identifying conditions in which it is better to use qualitative tools, as well as conditions that demand formal quantitative modeling, etc.

SD was based strictly on building quantitative models to last for a long period of time. Although SD models are a mathematical representation of problems and policy alternative, for the most part, the available information is not numerical by nature, it is rather

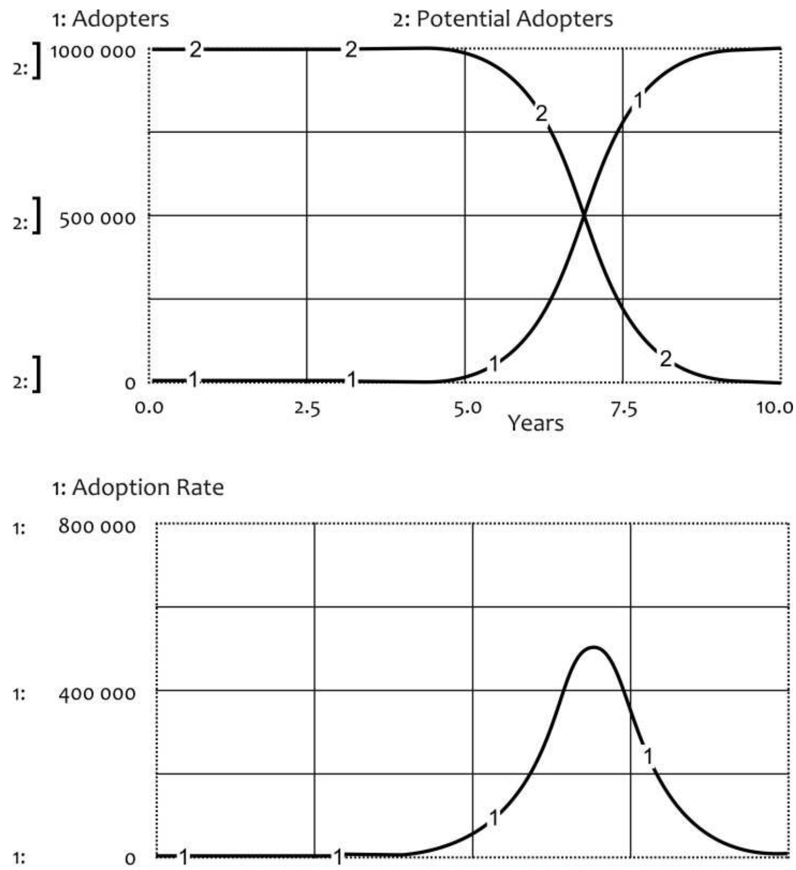

Figure 3 Dynamics of product adoption by the word-of-mouth

Source: Morecroft, 2007, 170

qualitative. In spite of a general agreement on the importance of qualitative data and tools during the SD models development, there are no clear descriptions of the purpose and time of their using.

The lack of an integrated set of procedures for acquiring and analyzing qualitative information makes a gap between the modeled problem and the problem model. The gap is even more visible when a model considers the use of the soft variables, such as consumers' satisfactions or products quality. Problems connected with the quantification and formulation of qualitative variables has led to the development of the qualitative SD (Coyle, 2000; Homer & Oliva, 2001; Luna Reys & Anderson 2003; Dhawan et al, 2011). In that sense, certain diagrams, such as causal loop diagrams, can be used as qualitative tools for policy conclusions without quantification and simulation (Coyle, 2000, 233).

However, there is a question if certain qualitative tools should be used with or without additional quantification and simulation. Although there are situations where qualitative instruments are used without additional quantification and simulation, simulation is almost always considered to be wanted in a policy analysis, even when there are some uncertainties and soft variables. In fact, it is necessary that a danger of conclusions made only according to qualitative tools as well as the limitations of the simulation models be recognized and understood. (Homer & Oliva, 2001). Some researches on the effects of the quantitative and qualitative modeling in SD demonstrate the fact that, for relatively simple problems, represented by simple diagrams, it is enough to use qualitative modeling tools in SD. On the other hand, for complex assignments, it is necessary that quantitative models and simulation be included (Dhawan et al., 2011, 321). In spite of the fact that quantification is useful, one should carefully try to quantify soft variables. This is about a research field extremely important for a further development of SD (Coyle 2001, 362).

It could also be concluded that the question of using qualitative data and tools in SD is not an adequate one. The adequate ones would be where and how. Although certain authors think that the significance of qualitative data mostly stands out in the conceptualization phase, and less in the model formulating phase, qualitative data are present in all phases of the modeling process (Luna – Reyes & Andersen, 2003, 275). According to that, some of the key techniques for collecting qualitative data can be identified in each modeling phase – such as interview, Delphi technique, the nominal group technique, etc. (Luna Reyes & Andersen 2003, 287 – 292).

Another type of critiques in SD is connected with the unitary nature of management problem situations, i.e. the functionalist systems paradigm which is the base for SD. Problem situations in organizations represent certain subjective constructions and participant interpretations, because the identifying of certain structures considers a continual process of negotiating with participants i.e. clients in the modeling process. In the given context, a tendency to research an SD system objectively, from outside the system, with a help of models built on the feedback process, represents a very complex task to do. Also, in SD, we start with the fact that there is accordance upon the model purpose, which neglects the purpose and aim variety that different participants have in management problems solving (Jackson, 2003, 81).

Group model–building arises as a response to these critiques (Vennix, 1995; Vennix 1999; Rouwette, 2001) or participative modeling (Lane, 2010), which is trying to include different participants, i.e. clients perceptions and opinions, in the model-building process. This is, in fact, an attempt to apply SD to some insufficiently defined, i.e. unstructured problems, and in that way to approach an interpretative paradigmThe research of certain cognitive limitations, i.e. ways for increasing capacity of group data processing, on the one hand, and the way participants see and interpret different problem situations, on the other, are important in researching the group model-building effectiveness in unstructured problem situations (Vennix, 1999, 381).

In order to effectively face the unstructured problems the system dynamicists should, above all, accept the fact that in many situations it is not useful, or that all the phases of the modeling process are even impossible to use. As previously stated, in some situations, it is better to apply only certain qualitative tools without quantification and simulation (Coyle, 2000, Dhawan et al, 2011). The fact is that it is necessary to precisely estimate the conditions and effects of the qualitative and quantitative modeling.

Beside the stated, it is necessary that different ways of inducing the team learning and effective communication within the groups be expored to improve the modeling process. To ensure learning, participants have to become modelers. It is necessary that the participants take an active part in a model development to enable effective model learning. Generally, in estimating the group model-building effectiveness, it can be concluded that participating in the modeling process increases clients' commitment and makes the implementation easier (Rouwette, 2001, 32, Vennix, 1995, 55).

However, tending to approach the interpretive paradigm, SD risks losing its key functionalist feature to identify laws that govern the behavior of systems. It means that, above all, SD should keep its functionalist characteristics (Jackson, 2003, 81). In fact, certain knowledge and skills necessary for model building in SD should be combined with the appropriate skills and knowledge necessary for facilitating participation and negotiation within groups (Vennix, 1999, 392).

Certain SD deficiencies can be overcome by a combined use of SD and some other interpretive systems approaches, such as Soft System Methodology (Coyle & Alexander, 1996; Lane & Oliva, 1998; Rodriguez Ulloa & Paucar – Caceras, 2005). Besides, SD can be combined with other functionalist approaches such as Organizational Cybernetics (Schwaninger, 2004; Schwaninger & Perez Rios, 2008).

CONCLUSION

SD, as a relevant structuralist–functionalist systems methodology, is based on the theory of information feedback and control. It is adequate for solving complex – unitary management problems, i.e. problem situations. Management problem situations in SD are expressed by the feedback structure and the process within, represented by appropriate diagrams and mathematical system models.

SD models represent an extremely powerful tool for management problems solving within organizations. Developed through an appropriate modeling process, the SD model can be used in redesigning adequate organization polices and/or structures. The modeling process itself is an extremely complex iterative process of the modeler's moving through certain phases. Although there are different classifications of the modeling process phases, the following phases can be identified: the conceptualization phase, i.e. identifying a problem and presenting it by feedback loops; the formulating phase, i.e. the phase of building a mathematical model represented by appropriate level and rate equations; the testing phase or model validation by comparing it to the realistic world; and the implementation phase, i.e. model application in designing policies for improving the results for an organization's functioning.

Based on the assumption that the structure generates a certain behavior, SD models enable the prediction of a future system behavior through computer simulations, which is shown on the example of a new product adoption on the market. The key hypothesis in the paper can be confirmed by researching the theoretical-methodological and applicative aspects of management problems modeling within the conceptual framework of SD.

In spite of a great number of successful SD model applications in management problems solving, the SD models have certain limitations. This is about different problems connected with the quantification of certain soft variables and possible imprecisions and mistakes to follow. Qualitative SD or qualitative modeling in SD accentuating the significance of a single or combined use of certain qualitative and quantitative tools in SD come to surface as a response to these deficiencies. The limitations connected with the functionalist paradigm which SD is based on, should also be mentioned. It is related to the fact that SD assumes the existence of accordance on the model purpose, by which different perceptions and clients i.e. participants in the modeling process are neglected. In that sense, there are tendencies that SD approaches to the interpretive paradigm through group model-building. Despite the fact that soft variables and participants' perceptions should be included in research, SD should not lose its key structuralist-functionalist features in tending to approach the interpretive paradigm.

Bearing in mind the identified deficiencies of SD and its models, it is necessary that different assumptions, conditions, and ways of a combined use of SD and other systems approaches to management be researched. SD can be used in combination with appropriate interpretive systems methodologies such as Soft System Methodology (SSM), where SD models represent an adequate support to SSM tools in research of organizations` structures and their functioning. Besides, SD could be combined with systems approaches that also belong to the functionalist systems paradigm, such as Organizational Cybernetics. A combined SD use, i.e. the SD model use with other methodologies, methods and techniques, represents a special field relevant for future researches.

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