System Dynamics Modeling: Validation for Quality Assurance

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Article Outline

Glossary

Model/model system A model is an abstract representation of a concrete ("real") system. Models can be descriptive or prescriptive (normative). Their functions can be to enable explanation, anticipation, or design. A distinction used in this contribution is between causal and noncausal models, with System Dynamics models being of the former type. The term *model system* is used to stress the systemic character of a model; this serves to identify it as an organized whole of variables and relationships, on the one hand, and to distinguish it from the *real system* which is to be modeled, on the other.

Model validity A model's property of reflecting adequately the system modeled. Validity is the main feature of model quality. It is a matter of degree, not a dichotomized property.

Model purpose The goal for which a model is designed or the function it is supposed to fulfill. The model purpose adheres closely to the end-model user or model owner. Model purpose is the criterion for the choice of a model's boundary and design.

Modeling process The process involving phases such as problem articulation, boundary selection, development of a dynamic hypothesis, model formulation, model testing, policy formulation, and policy evaluation (Sterman 2000). The modeling process is followed by model use and implementation, i.e., the realization of actions designed or facilitated by the use of the model.

Validation process Validation is the process by which model validity is enhanced systematically. It consists in gradually building confidence in the usefulness of a model by applying validation tests as outlined in this entry. In principle, validation pervades all phases of the modeling process and, in addition, reaches into the phases of model implementation and use.

Introduction

The present entry addresses the question of building better models. This is crucial for coping with complexity in general and in particular for the management of dynamic systems (Schwaninger 2010). Both the epistemological and the methodological-technological aspects of model validation for the achievement of high-quality models are discussed. The focus is on formal models, i.e., those formulated in a stringent, logical, and mostly mathematical language.

The etymological root of "valid" is in the Latin word "validus," which denotes attributes such as strong, powerful, and firm. A valid model, then, is well founded and difficult to reject because it accurately represents the perceived real system which it is supposed to reflect. This system can be either one that already exists or one that is

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being constructed, or even anticipated, by a modeler or a group of modelers.

The validation standards in System Dynamics are more rigorous than those of many other methodologies. Let us distinguish between two types of mathematical models, which are fundamentally different: causal, theory-like models and noncausal, statistical (correlational) models (Barlas and Carpenter 1990). The former are explanatory, i.e., they embody theory about the functioning of a real system. The latter are descriptive and express observed associations among different elements of a real system. System Dynamics models are causal models.

Noncausal models are tested globally, in that the statistical fit between model and data series from the real system under study is assessed. If the fit is satisfactory, the model is considered to be accurate ("valid," "true"). In contrast, system dynamicists postulate that models be not only right but right for the right reasons. As the models are made up of causal interdependencies, accuracy is required for each and every variable and relationship. The following principle applies: In case only one component of the model is shown to be wrong, the whole model is rejected even if the overall model output fits the data (Barlas and Carpenter 1990). This strict standard is conducive to high-quality modeling practice.

A model is an abstract version of a perceived reality. Simulation is a way of experimenting with mathematical models to gain insights and to employ these to improve the real system under study. It is often said that System Dynamics models should portray problems or issues, not systems. This statement must be interpreted in the sense that one should not try to set the boundaries of the model too wide, but rather give the model a focus by concentrating on an object in accordance with the specific purpose of the model. In a narrower definition, even an issue or problem can be conceived of as a "system," i.e., "a portion of the world sufficiently well defined to be the subject of study" (Rapoport 1954). Validity then consists in a stringent correspondence between model system and "real system."

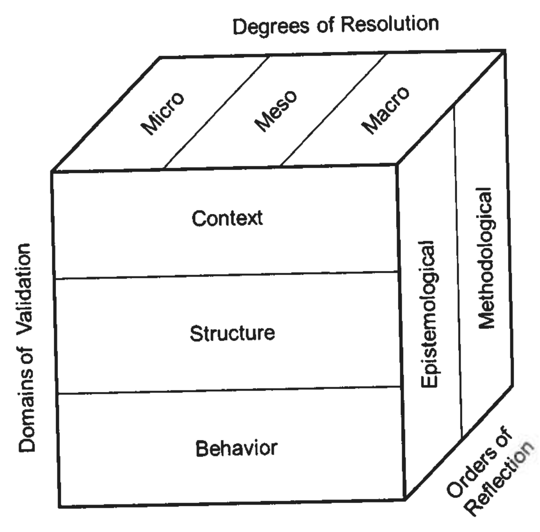
We will treat the issue of model validation as a means of assuring high-quality models. We interject that validity is not the only criterion of model quality, the other criteria being parsimony, ease of use, practicality, importance, etc. (Schwaninger and Groesser 2008).

In the following, the epistemological foundations of model validity are reviewed (section "Epistemological Foundations"). Then, an overview of the methods for assuring model validity is given (section "Validation Methods"). Further, the survey includes an overview of the validation process (section "Validation Process") and our final conclusions (section "Synopsis and Outlook").

The substance of this entry will be made more tangible by means of the following frame of reference. We call it the validation cube. The diagram in Fig. 1 shows three dimensions of the validation topic:

Orders of reflection: The two layers addressed are *methodology* and *epistemology, at a meta-level.* These define the objects of the next two sections "Epistemological Foundations" and "Validation Methods."

Domains of validation: The three domains, *context, structure*, and *behavior*, refer to the groups of validation methods as described in the section on "Validation Methods."



System Dynamics Modeling: Validation for Quality Assurance, Fig. 1 The validation cube – a frame of reference showing three dimensions of the validation topic

Degrees of resolution: We address the different granularities of models. *Micro* refers to the smallest building blocks of models (e.g., variables or small sets of variables), *meso* to modules which constitute a model, and *macro* to the model as a whole.

Epistemological Foundations

Epistemology is the theory that enquires into the nature and grounds of knowledge: "What can we know and how do we know it?" (Lacey 1996). These questions are of utmost importance when dealing with models and their validity, because a method of validation is only as good as its epistemological basis.

We can only briefly refer to the antecedents of the epistemological perspective inherent in the idea of model validation as commonly held today in the community of system dynamicists. One could go back to Socrates who, in Plato's Republic (fourth century BC), addressed the problematic relationship between reality, image, and knowledge. One could also refer to John Locke (seventeenth century), the first British empiricist who maintained that ideas could come only from experience, while admitting that our knowledge about external objects is uncertain. We will address the philosophical movements of the nineteenth and twentieth centuries, which are direct sources of the epistemology that is important for model validation. The reader may kindly excuse us for certain massive retrenchments that we are obliged to take.

What will be said here about theories applies equally to formal models. In System Dynamics, models either embody theories or they are considered essential components of theories. In addition, processes of modeling and theory building are of the same nature; a model, like any theory, is built and improved in a dialectic of propositions and refutations (Schwaninger and Groesser 2008).

Positivism and Critique

Positivism is a scientific doctrine founded by Auguste Comte (nineteenth century) which raises the *positive* to the principle of all scientific knowledge. "Positive," in this context, is not meant to be the opposite of negative, but the given, factual, or indubitably existent. The positive is associated with features such as being real, useful, certain, and precise. Positivism confines science to the observable and manipulable, drawing on the mathematical, empirical orientation of the natural sciences as its paragon. The objectivist claim of positivism is that things exist independently of the mind and that truths are detached from human values and beliefs. This stance calls for models that approximate an objective reality.

A younger development in this vein is the school of logical positivism, also logical empiricism (with Schlick, Neurath, Hempel, etc.), which concentrates on the problem of meaning and has developed the verifiability principle: Something is meaningful only if verifiable empirically, i.e., ultimately by observation through the senses. Verify here means to show to be true (Lacey 1996). For the logical positivists, the method of verification is the essence of theory building. Tests of theories hinge on the confirmation by facts. In SD, testing models on real-world data is a core component of validation.

Positivism has been criticized for being reductionist, i.e., for its tendency to reduce concepts to simpler or empirically more accessible ones and to conceive of learning as an accumulation of particular details. The critique has also interjected that there is no theory-independent identification of facts, and therefore different theories cannot be tested by means of the same data (Feyerabend 1993). Another objection maintains that social facts are not merely given, but produced by human action, and that they are subject to interpretation (Seiffert and Radnitzky 1994). These arguments introduce the principle of relativity, which is of crucial importance for the ambit of model validation: A model is a subjective construction by an observer.

Pragmatism: A Challenge to Positivism

Pragmatism, which arose in the second half of the nineteenth century, emphasizes action and the practical consequences of thinking. Its founder Charles Sanders Peirce was interested in the effects that the meaning of scientific concepts could have on human experience and action. He defined truth as "the opinion which is fated to be ultimately agreed to by all who investigate" (cit. Lacey 1996), whereby truth is linked to consensual validation. For pragmatists truth is in what works (Ferdinand Schiller) or satisfies us (John Dewey) and what we find believable and consistent: "'The true' . . . is only the expedient in the way of our thinking," and "truth is *made* . . . in the course of experience" (James 1987: 583, 581).

Pragmatism is often erroneously disdained for supposedly being a crass variety of utilitarianism and embodying a crude instrumentalist rationality. A more accurate view considers the fact that pragmatists are not satisfied with a mere ascertainment of truth; instead they ask: "If an idea or assumption is true, does this make a concrete difference to the life of people? How can this truth be actualized?" In other words, pragmatism does not crudely equalize truth and utility. It rather postulates that those truths which are useful to people ought to be put into practice (Seiffert and Radnitzky 1994).

Pragmatism introduces the criteria of confidence and usefulness, which are more operational as guides to the evaluation of experiments than is the notion of an absolute truth, which is unattainable in the realm of human affairs. At the same time, pragmatism triggers a crucial insight for the context of model building: The validity of a model depends not only on the absolute quality of that model but also hinges on its suitability with respect to a purpose (Forrester 1961). In the context of model validation, then, truth is a relative property; more exactly, a *truth* holds for a limited domain only.

More Challenges to Positivism

We discuss three more challenges to positivism in the twentieth century. The first is Thomas Kuhn's theory of scientific revolutions (Kuhn 1996): Kuhn shows, by means of historical cases, that in the sphere of science, generally accepted ways of looking at the world ("paradigms") change over time through fundamental shifts. Therefore, the activities of a scientist are largely shaped by the dominant scientific worldview. Second, Willard Van Orman Quine and Wilfrid Sellars argue that knowledge creation and theory building is a holistic, conversational process, as opposed to the reductionist and confrontational views (Barlas and Carpenter 1990).

Both of these movements contribute to our understanding of how real systems are to be modeled and validated, as organized wholes, and consciously with respect to the values and beliefs underlying a given modeling process. This approach adheres to the spirit of models themselves, by means of which the behavior of whole systems can be simulated and tested on their inherent assumptions.

A third challenge are the interpretive streams of epistemology (for an overview, see Heracleous (2006)). Among them, a main force which expands the possibilities of scientific methodologies is the strand of hermeneutics. Derived from the Greek *hermeneuein* – to interpret or to explain – the term *hermeneutics* stands for a school, mainly associated with Hans-Georg Gadamer, which pursues the ideal of a human science of understanding. The emphasis is on interpretation in an interplay between a subject-matter and the interpreter's position. This emphasis introduces the subjective into scientific methodology. Hermeneutics denies both that a single "objective true interpretation" can transcend all individual viewpoints and that humans are forever confined within their own ken (Lacey 1996). This epistemology offers a necessary complement to a scientific stance, which exclusively hinges on "hard," quantitative methods in order supposedly to achieve absolute objectivity. The implication of hermeneutics for model validation is that it recognizes the pertinence of subjective judgment. In this connection, interpretive discourses play a crucial role in group model building and validation. Such discourses lead beyond the subjective, entailing the creation of intersubjective, shared realities. We will revert to this factor in section "Validation Process."

Critical Rationalism

Critical rationalism is a philosophical position founded by Karl R. Popper (1959, 1972). It grew out of positivism but rejected its verificationist stance. Critical rationalism posits that, in the social domain, theories can never be definitely proved, but can only reach greater or lesser levels of truth. Scientific proofs are confined to the realm of the formal sciences, namely logic and mathematics.

As Popper demonstrates, all theories are provisional. As a consequence, the main criterion for the assessment of a theory's truth status is *falsification* (Popper 1959). A theory holds as long as it is not refuted. Consequently, any theory can be upheld as long as it passes the test of falsification. In other words, the fertile approaches to science are not those of corroboration but the falsificationist efforts to test if the theory can be upheld. In the context of modeling this means that validation must undertake attempts to falsify a model, thereby testing its robustness.

Even Popper's theory of science is not unchallenged. For example, Kuhn has made the point that its principles are applicable only to normal science, which operates incrementally within a given paradigm, but not to anomalous science, which uncovers unsuspected phenomena in periods of scientific revolution (Kuhn 1996). This observation has an implication for model validation: Alternative and even multiple model designs should be assessed for their ability to account for fundamental change.

On the Meaning of Validity and Validation

One of the predominant convictions about science is the obsessive idea that proofs are the touchstone of the validity of both theories and models. We follow a different rationale, reverting to the philosophy of science as embodied in critical rationalism.

Popper's refutationist concept (as opposed to a verificationist concept) of theory-testing implies both an evolutionist perspective and an empiricist stance. The evolutionist perspective is primary because it welcomes the challenges posed to a theory, since these attempts at falsification lead to an evolutionary process: Successful falsification efforts result in revisions and improvements of the theory. Correspondingly, empiricism is paramount in the social sciences, because the main source for the refutation of a theory is empirical evidence. However, falsification can also be grounded in logical arguments where empirical evidence cannot be obtained. In this sense, a structuralist approach as used in System Dynamics validation transcends the bounds of logical empiricism.

As a consequence of the evolutionist perspective, there is no such thing as absolute validity. Validity is always imperfect, but it can be improved over time. The empiricist aspect of theory building implies that theories must be validated by means of empirical data. However, logical assay, estimation, and judgment are complementary to this empiricist component (see below).

A validation process is about gradually building confidence in the model under study (Barlas 1996). This is both analytical and synthetic. It is directed at the model as a whole as much as it is at the components of the model. The touchstone of validity is less whether the model is right or wrong: As John Sterman states, ". . . all models are wrong" (Sterman 2000). Some models, however, fulfill the purpose ascribed to them, i.e., they are useful. Models are inherently incomplete; they cannot claim to be true in an absolute sense, but only to be relatively true (Barlas and Carpenter 1990). In this sense, *validation* is a *goal-oriented* activity and *validity* a *relative* concept.

Finally, the validation process often involves several people because the necessary knowledge is distributed. In these cases, the dialectics of propositions and refutations, as well as the interaction of different subjective viewpoints, and consensus-building, are integral. Validation processes, then, are semiformal, discursive social procedures with a holistic as opposed to a fragmentary orientation (ibidem).

On Objectivity

If subjective views and judgments are as prominent as alleged above, does objectivity play a role at all? Operational philosophy shows a way out of this dilemma: Anatol Rapoport defines objectivity as "invariance with respect to different observers" (Rapoport 1954). Popper has a similar stance in proposing that general statements must be formulated in a way that they can be criticized and, where applicable, falsified (Popper 1972). This concept of objectivity is a challenge to model validation: When defining concepts and functions, one must first of all strive for falsifiable statements. In principle, formal models meet this criterion: each variable and every function or relationship can be challenged. And they must be challenged, so that their robustness can be tested. The duty, then, is in finding the invariances that are intersubjectively accepted as the best approximations to truth. Frequently this is best achieved in group model-building processes (Vennix 1996). Finally, truth is something we search for but do not possess (Popper 1972), i.e., even an accepted model cannot guarantee truth with final certainty.

Validation Methods

For the enhancement of model validity, a considerable set of qualitative and quantitative tests has been developed. The state of the art has been documented in seminal publications (e.g., Forrester 1961, Forrester and Senge 1980, Barlas and Carpenter 1990, Petersen and Eberlein 1994, Lane 1995, Barlas 1996, Sterman 2000). Our purpose here is to present and exemplify the different tests to encourage and help those who strive to develop high-quality System Dynamics models.

In the following, an overview of the types of tests developed for System Dynamics models is given, without any claim to completeness. These tests have been documented extensively in Forrester (1961), Forrester and Senge (1980), Barlas (1996), and Sterman (2000). The descriptions of the tests adhere closely to the specifications of these authors (mainly Forrester and Senge). In addition, we have developed a new category for tests that concentrate on the context in which the model is to be developed. High-quality models can be created only if the relevant context is taken into consideration. To facilitate orientation, we have attached an overview of all described tests in the Appendix.

In this section, we are describing three groups of tests, those related to model-related context, tests of model structure, and tests of model behavior. Many of the tests described in the following can be utilized for explanatory analysis which aims at an understanding of the problematic behavior of the issue under study. Others are suitable for normative ends, in analysis targeted on improvements of system performance with regard to a specified objective of the reference system. Also known as policy tests, or policy analysis, these "tests of policy implications differ from other tests in their explicit focus on comparing changes in a model and in the corresponding reality. Policy ... tests attempt to verify that response of a real system to a policy change would correspond to the response predicted by the model" (Forrester and Senge 1980). Policy testing can show the risk involved in adopting the model for policy making.

Tests About Model-Related Context

These tests deal with aspects related to the situation in which the model is to be developed and embedded. They imply metalevel decisions which have to be taken in the first place, before engaging in model building. Applied ex post facto, i.e., after modeling, they allow for assessing the utility of the modeling endeavor as such. These tests are extremely important, because they can help avoid ill-conceived models and the use of modeling methods which are inappropriate for dealing with the issues at hand. Model obsolescence is often due not only to flaws in the details of structure specifications but also and first of all because the wrong solution is applied to the problem under study.

Test of Model Framing

Framing means first of all to state an orientative purpose and clear goal(s) for the model. Related to this is the demarcation of the audience: mainly the user(s) of the model. Is it for managers, politicians, etc., and at what levels? What should be learned, and which kinds of insights should be gained from using the model? These decisions clarify the model's boundaries.

Issue Identification Test

The *raison d'être* of a System Dynamics model is its ability to adequately address an issue and to enhance stakeholders' understanding, an ability

which may lead to policy insights and system improvements. The issue identification test examines whether or not the identified issue or problem is indeed meaningful. Has the "right" problem been identified? Does the problem statement address the origins of an issue or only superficial *symptoms?* Whenever complex issues are addressed by a model, different perspectives (e.g., professional, economic, political) must be integrated for an accurate problem identification and modeling. This is not a "one-shot-only" test; it has to be applied recurrently during the modeling procedure. By reflecting regularly on the correctness of the identified issue, the modeler can increase the likelihood of capturing the origins of a suboptimal system behavior.

Adequacy of Methodology Test

Simulation models respond to the limitations of humans' mental ability to comprehend complex, dynamic feedback systems (Sterman 1989). The adequacy of methodology test scrutinizes whether the System Dynamics methodology is best-suited for dealing with the issue under study. One needs to clearly ascertain if that issue is characterized by dynamic complexity, feedback mechanisms, nonlinear interdependency of structural elements, and delays between causes and effects. One needs to ask also if the issue under study could be better addressed by another methodology. For example, in a case where the question is to understand the difference in numerical outcomes between two configurations of a production system, it lets one determine whether discrete event simulation would fulfill this requirement more accurately than System Dynamics.

System Configuration Test

This test asks the fundamental question about whether the structural configuration chosen can be accepted. It challenges the assumption that the model represents the actual working of the system under study. The eventuality of a different design would be indicated to capture new conditions, such as different system configurations, phenomena, or rules of the game. Even revolutionary changes might be considered. Such an outlook may require a totally new model or an alternative model designed from a different vantage point. This would at least feasibly approximate the need to take paradigmatic change into account.

System Improvement Test

The purpose of modeling is to understand a part of reality and to resolve an issue. The system improvement test can be performed only after the modeling project (ex post facto test), once the insights derived from the model have already been implemented in the real system. This test reestablishes the connection between the abstract mathematical model and the real system. The system improvement test helps to evaluate whether or not the model development was successful. In operational terms, any improvements of the real system under study have to be compared with explicit objectives. In practice, the test might assess the impact of the modeling process or the model use either on the mental models of decision makers or on changes in organization structures. In principle, assessing the impact of a modeling endeavor is very difficult (one preliminary example is provided by Snabe and Grössler 2006).

Tests of Model Structure

Tests of model structure refer to the "nuts and bolts" of System Dynamics modeling, i.e., to the formal concepts and interrelationships which represent the real system. Model structure tests aim to increase confidence in the structure of the created theory about the behavior mode of interest. The model structure can be assessed by means of either direct or indirect inspection. Tests of model structure assess if the logic of the model is attuned to the corresponding structure in the real world. They do not yet compare the model behavior with time series data from the real system.

Direct Structure Tests

Direct structure tests assess whether or not the model structure conforms to relevant descriptive knowledge about the real system or class of systems under study. In principle they can be carried out without computers. By means of direct comparison, they qualitatively assess any disparities between the original system structure and the model structure.

Structure Examination Test Examination in this case means comparison in the sense just outlined. Qualitative or quantitative information about the real system structure can be obtained either empirically or theoretically. In the empirical version, structure examination tests compare the form of equations in the model with the relationships extant in the real system (Barlas 1996). They include reviews of model assumptions about system elements and their interdependencies, e.g., reviews made by highly knowledgeable experts of the real system. Theory-based tests compare the model structure with theoretical knowledge from literature about the type of system being studied.

To pass the structure examination test, the model must not contradict either the evidence or knowledge about the structure of the real system. This test ensures that the model contains only those structural elements and interconnections that are most likely extant in the real system. In this context, formal inspections of the model's equations, reviews of the syntax for the stock and flow diagram, and walkthroughs along the causal loop diagrams and their embodied causal explanations may be indicated. The experienced reader might recommend the use of statistical tests to identify and validate model structure. As Forrester and Senge (1980) indicate, a long-standing discussion exists about the application of inferential statistical tests for structure examination. After a series of experiments, Forrester and Senge conclude "that conventional statistical tests of model structure are not sufficient grounds for rejecting the causal hypotheses in a system dynamics model" (Forrester and Senge 1980). In the future, however, new statistical approaches might enrich the testing procedures.

Parameter Examination Test A parameter is a quantity that characterizes a system and is held constant in a case under study but may be varied in different cases (e.g., energy consumption per capita per day). The aim of parameter examination is to evaluate a model's parameters against evidence or knowledge about the real system. The test can utilize both empirical and theoretical information. Furthermore, the test can be conceptual or numerical. The conceptual parameter examination test is about construct validity; it identifies elements in the real system that correspond to the parameters of the model. Conceptual correspondence means that the parameters match elements of the real system's structure. Numerical parameter examination checks to see if the quantities of the conceptually confirmed parameters are estimated accurately. Techniques for the estimation of parameters are described in Graham (1980) and Struben et al. (2015).

Direct Extreme Condition Test Extreme conditions do not often occur in reality; they are exceptions. The validity of a model's equations under extreme conditions is evaluated by assessing the plausibility of the results generated by the model equations against the knowledge about what would happen under a similar condition in reality. Direct extreme condition testing is a mental process and does not involve computer simulation. Ideally, it is applied to each equation separately. It consists of assigning extreme values to the input variables of each equation. The values of the output variables are then interpreted in terms of what would happen in the real system under these extreme conditions. For example, if a population is zero, then neither births, deaths, nor consumption of resources can occur.

Boundary Adequacy Structure Test Boundary adequacy is given if the model contains the relevant structural relationships that are necessary and sufficient to satisfy a model's purpose. Consequently, the boundary adequacy test inquires whether the chosen level of aggregation is appropriate and if the model includes all relevant aspects of structure. It should ensure that the model contains the concepts that are important for addressing the problem endogenously. For instance, if parameters are likely to change over time, they should be endogenized (Forrester and Senge 1980). The pertinent validation question is: "Should this parameter be endogenized or not?" That question must be decided in view of the model's purpose.

The boundary adequacy test can be applied in three ways: as a structural test, as a behavioral test, and as a policy test. The names are correspondingly boundary adequacy structure test, boundary adequacy behavior test, and boundary adequacy policy test.

As a test of model structure, the boundary adequacy test involves developing a convincing hypothesis relating the proposed model structure to the particular issue addressed by the model. The boundary adequacy behavior/policy test (explained in the next section) continues this line of thinking.

Dimensional Consistency Test This test checks the dimensional consistency of measurement units of the expressions on both sides of an equation. The test is performed only at the equation level. In case all tests of the individual equations are passed, a large system of dimensionally consistent equations results. This test is only passed, if consistency is achieved without the use of parameters that have no meaning in respect to the real world. The dimensional consistency test is a powerful test to establish the internal validity of the model.

Indirect Structure Tests

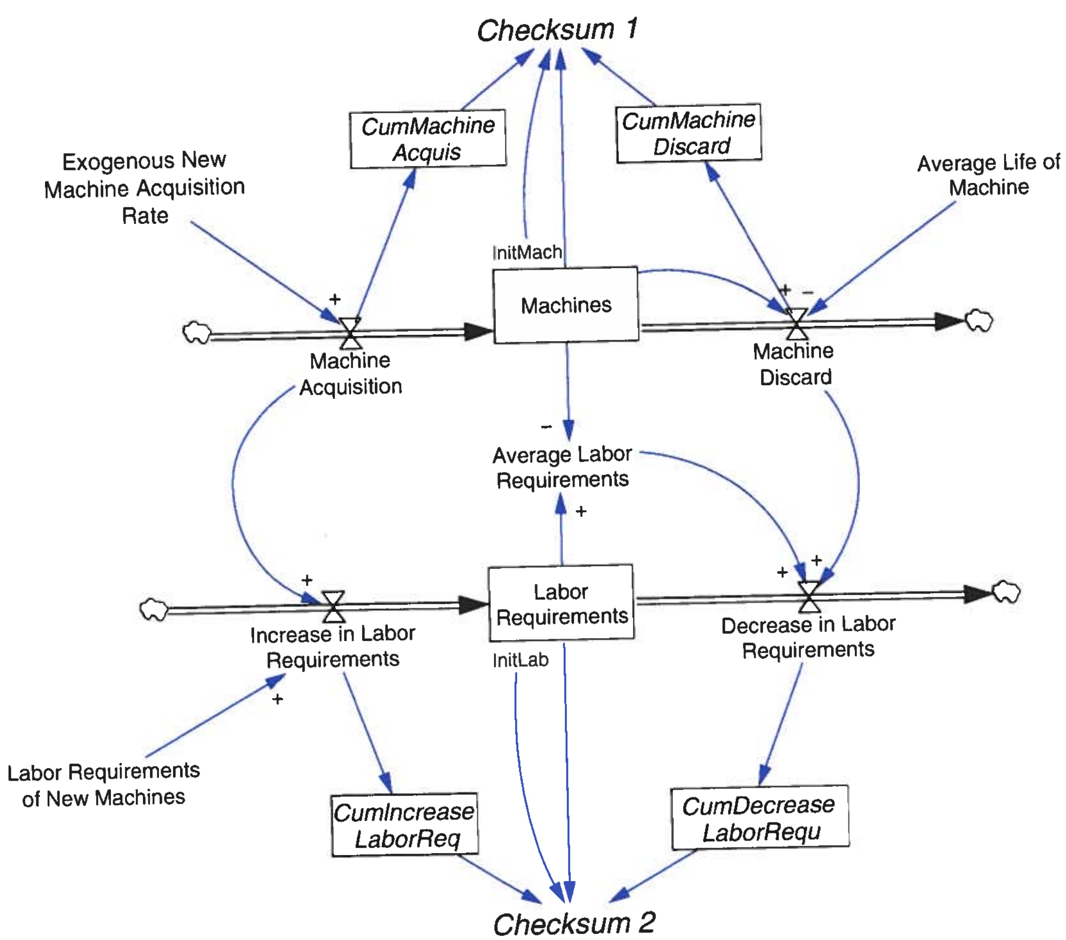
Indirect structure tests assess the validity of the model structure indirectly by examining model-generated outcome behaviors. These tests require computer simulation. The comparative activities in these tests are based on logical plausibility considerations which in turn are based on the mental models of the analyst. Comparisons of model-generated data and time series about the real system are not yet involved. The tests can be applied to different degrees of model completeness, i.e., to the smallest "atomic" model components, to sub-models, as well as to the entire model.

Mass-Balance Check This powerful test was elaborated, as follows, by Brian Dangerfield (2014): In a model that contains flows of resources, inflows and outflows must balance out, i.e., the model must not gain or lose mass. The more flows a model includes, the greater is the need for such a test. The procedure consists in accumulating all the inflows and outflows over time for each resource being modeled and then using the following balance or checksum equation:

$$\int_{t=0}^{tfinal} \Big[\mathrm{Sum}\,of\,\mathrm{all}\,in\,flows - \mathrm{Sum}\,of\,\mathrm{all}\,out\,flows + initial\ values\ of\ stocks - current\ values\ of\ stocks\Big] * \mathrm{dt} = 0$$

The correct result of the computation should be equivalent to zero throughout the run; anything else hints at a flawed model. (It is necessary to employ a double precision version of the software being utilized.) If more than one resource flow is involved (e.g., people and finance), then separate tests must be carried out for each flow. Figure 2 provides an example; in this model (Sterman 2000), a co-flow of labor requirements is tracked along an evolving structure of capital ("machines").

Indirect Extreme Condition Test For this test, the modeler assigns extreme values to selected model parameters and compares the generated model behavior to the observed or expected behavior of the real system under the same extreme condition. This test is the logical continuation of the direct extreme condition test, i.e., many of the extreme conditions mentally developed in the previous stage can now be deployed to evaluate the simulated behavioral consequences. This test can be used for the explanatory analysis phase of modeling but also for the normative phase of policy development. In the first instance, indirect extreme conditions are used to develop a structure that can reproduce the system behavior of interest and guard against developments impossible in reality. In the latter instance, the introduction of policies aims to improve the system's performance. The indirect extreme policy test introduces extreme policies to the model and compares the simulated consequences to what would be the most likely outcome of the real



System Dynamics Modeling: Validation for Quality Assurance, Fig. 2 Mass-balance check – example (model in standard characters, testing gear in italics)

system if the same extreme policies would have been implemented.

Behavior Sensitivity Test Sensitivity analysis assesses changes of model outcome behavior given a systematic variation of input parameters. This test reveals those parameters to which the model behavior is highly sensitive and asks if the real system would exhibit a similar sensitivity to changes in the corresponding parameters. "The behavior sensitivity test examines whether or not plausible shifts in model parameters can cause a model to fail behavior tests previously passed. To the extent that such alternative parameter values are not found, confidence in the model is enhanced" (Forrester and Senge 1980). A model can be numerically sensitive, i.e., the numerical values of variables change significantly, but the behavioral patterns are conserved. It can also exhibit behavioral sensitivity, i.e., the modes of model behavior change remarkably based on systematic parameter variations (Barlas (2006) defines several distinct patterns of model behavior).

As the test for indirect extreme conditions, the behavior sensitivity test can also be deployed to assess policy sensitivity. It can reveal the degree of robustness of model behavior and hence indicate to what degree model-based policy recommendations might be influenced by uncertainty in parameter values. If the same policies would be recommended regardless of parameter changes

over a plausible range, risk in using the model would be less than if two plausible sets of parameters lead to distinct policy recommendations.

Integration Error Test Integration error is the deviation between the analytical solution of differential equations and the numerical solution of difference equations. This test ascertains whether the model behavior is sensitive to changes in either the applied integration method or the chosen integration interval (often referred to as simulation time step). Euler's method is the simplest numerical technique for solving ordinary differential and difference equations. For models that require more precise integration processes, the more elaborated Runge-Kutta integration methods can produce more accurate results, but they require more computational resources.

Boundary Adequacy Behavior Test/Boundary Adequacy Policy Test The logic for testing the boundary adequacy has already been developed under the aspect of direct structure testing in the preceding section. The indirect structure version of this test asks whether the model behavior would change significantly if the boundary were extended or reduced; i.e., the test involves conceptualizing additional structure or canceling unnecessary structure with regard to the purpose of the study. As one example of expanding the model boundary, this version of the test allows one to detail the treatment of model assumptions considered as unrealistically simple but still important for the model purpose. On the other hand, simplifying the model is also a way to reduce the model boundary. The loop-knockout analysis is a useful method to implement this two-sided test. Knockout analysis checks behavior changes induced by the connection and disconnection of a portion of the model structure and helps the modelers to evaluate the usefulness of those changes with respect to the model purpose.

The other version of this test is the boundary adequacy policy test. It examines whether policy recommendations would change significantly if the boundary were extended (or restricted): That is, what would happen if the boundary assumptions were relaxed (or confined)?

Loop Dominance Test Loop dominance analysis studies the internal mechanisms of a dynamic model and their temporal, relative contribution to the outcome behavior of the model. The relative contribution of a mechanism is a complex quantitative statement that explains the fraction of the analyzed behavior mode caused by the considered mechanism (see Kampmann and Oliva 2018). The analysis reveals the relative strengths of the feedback loops in the model. The loop dominance test compares these results with the modeler's or client's assumption about which are the dominant feedback loops in the real system. Since the results are analytical statements, interpretation and comparison with the real system require profound knowledge about the system under study.

Loop dominance analysis reveals insights about a model on a different level of analysis than the other validation tests discussed so far: It works not on the level of individual concepts or behaviors of variables but on the level of causal structure and compares the temporal significance of the different structures to each other. This test has developed from basic concepts (Richardson 1995) to sophistiated methods of analysis (Kampmann and Oliva op.cit.). If the relative loop dominances of the model map the relative loop dominances of the real system, confidence in the model is enhanced. In case the relative loop dominances of the real system are not known, it is still possible to evaluate whether or not the loop dominance logic in the model is reasonable.

Tests of Model Behavior

Tests of model behavior are empirical and compare simulation outcomes with data from the real system under study. On that basis, inferences about the adequacy of the model can be made. The empirical data can either be historical or refer to reasonable expectations about possible future developments.

Behavior Reproduction Tests

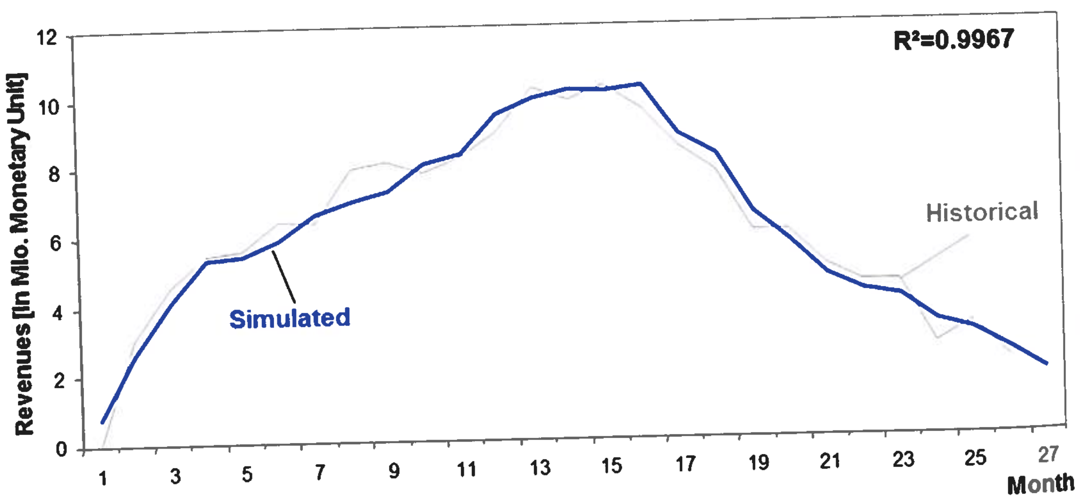
The family of behavior reproduction tests examines how well model-generated behavior matches the observed historical behavior of the real system. As a principle, models should be tested against data not only from periods of stability but also from unstable phases. Policies should not be designed or tested on the premise of normality, but rather should be validated with a view toward robustness and adaptiveness.

Symptom Generation Test This test indicates whether or not a model produces the symptom of difficulty that motivated the construction of the model. To pass the symptom generation test is a prerequisite for considering policy changes, because "unless one can show how internal policies and structures cause the symptoms, one is in a poor position to alter those causes" (Forrester and Senge 1980).

Summary statistics that measure and enable the interpretation of quantitative deviations provide the means to operationalize the symptom generation test. One known example is Theil inequality statistics, which measures the mean square error (MSE) between the model-generated behavior and historical time series data. It decomposes the deviation in three sources of error: bias (U_M), unequal variation (U_S), and unequal covariation (U_C) (Sterman 1984). An example taken from Schwaninger and Groesser (2008) illustrates the interpretation of the error sources.

The case in point, based on an example from an industrial firm, concerns the design of a model that replicates the historical product life-cycle pattern, as observed in the enterprise, with high accuracy (Fig. 3). "Product revenue" is the main variable of interest and specifies the symptom (growth phase followed by rapid decay). The mean-square error for revenues is 0.35. The individual components of the inequality statistics are $U_M = 0.01$, $U_S = 0.01$, $U_C = 0.98$. The decomposition shows that the major part of the error is due to the unequal covariation component, while the other two sources of error are small. This signifies that the point-by-point values of the simulated and the historical data do not match, even though the model captures the dominant trend and the average values in the historical data. Such a situation indicates that the major part of the error is probably unsystematic and therefore that the model should not be rejected for failing to match the noise component of the data. The residuals of the historic and simulated time series show no significant trend. This strengthens the assessment that the model comprises of a structure that captures the fundamental dynamics of the issue under study.

Frequency Generation and Phase Relationship Tests These tests focus on the frequency and phase relationships between variables. An example is the pattern of investment cycles in an industry. These tests are superior to point-by-point comparisons between model-generated and observed behavior (Forrester 1961).



System Dynamics Modeling: Validation for Quality Assurance, Fig. 3 Comparison of historical and simulated time series for the product revenues – example. The explained variance is close to 100% ($R^2 = 0.9967$)

Frequency refers to periodicities of fluctuation in a time series. Phase relationship is the relationship between the time series of at least two variables. In principle, three-phase relations are possible: preceding, simultaneous, and successive. The frequency generation test evaluates whether or not the periodicity of a variable is in accordance with the real system. The phase relationship test assesses the phase shifts of at least two variables by comparing their trajectories.

If the phase shift between the selected simulation variables contradicts the phase shift between the same variables as observed or expected in the real system, a structural flaw in the model might be diagnosed. The test can uncover failures in the model but offers only little guidance as to where the erroneous part of the model might be. The autocorrelation function test is one way to operationalize the frequency generation test (Barlas 1990). The function test consists in comparing the autocorrelation functions of the observed and the model-generated behavior outputs and can detect if significant errors between them exist.

Modified Behavior Test Modified behavior can arise from a modified model structure or changes in parameter values. This test concerns changes in the model structure. It can be performed if data about the behavior of a structurally modified version of the real system are available. "The model passes this test if it can generate similar modified behavior, when simulated with structural modifications that reflect the structure of the 'modified' real system" (Barlas 1996). The applicability of this test is rather limited since it requires specific data about the modified real system which must be similar in kind to the original real system. Only under this condition can additional insights into the suitability of the original model structure be obtained. If the modified real system deviates strongly from the original real system, the test does not result in any additional insights, because no stringent conclusions about the validity of the original system can be derived from a model that is dissimilar in its structure.

Multiple Modes Test A mode is a pattern of observed behavior. The multiple mode test considers whether a model is able to generate more than one mode of observed behavior, for instance, if a model about the production sector of an economy generates distinct patterns of fluctuations for the short term (production, employment, inventories, and prices) and for the long term (investment, capital stock) (Mass 1975). "A model able to generate two distinct periodicities of fluctuation observed in a real system provides the possibility for studying possible interaction of the mode and how policies differentially affect each mode" (Forrester and Senge 1980).

Behavior Characteristic Test Characteristics of a behavior are features of historical data that are clearly distinguishable, e.g., the peculiar shape of an oscillating time series, sharp peaks, long troughs, or such unusual events as an oil crisis. Since System Dynamics modeling is not about point prediction, the behavior characteristic test evaluates whether or not the model can generate the circumstances and behavior leading to the event. The creation of the exact time of the behavior is not part of the test.

Behavior Anticipation Tests

System Dynamics models do not strive to forecast future states of system variables. Nevertheless, given that the fundamental system structure is not subject to rapid and fundamental change, dynamic models might provide insights about the possible range of future behaviors. Hence, behavior anticipation tests are similar to behavior reproduction tests but possess a higher level of uncertainty.

Pattern Anticipation Test This test examines whether a model generates patterns of future behavior which are assumed to be qualitatively correct. The limits of anticipation are in that the structure of the system may change over time. The pattern anticipation test entails evaluation of periods, phase relationships, shape, or other characteristics of behavior anticipated by the model. One possibility for implementing this test is to split the historical time series into two data sets and introduce an artificial present time at the end of the first data series. The first set is then used for model development and calibration. The second data series is employed to perform the behavior anticipation test, i.e., to evaluate whether the model is able to anticipate the possible future behavior.

This test can also be used for policy considerations, in which case it is called "Changed Behavior Anticipation Test." It determines whether the model correctly anticipates how the behavior of the real system will change if a governing policy is changed.

Event Anticipation Test In respect to System Dynamics, the anticipation of events does not imply knowing the exact time at which the events occur; it rather means understanding the dynamic nature of events and being able to identify the antecedents leading to them. For instance, the event anticipation test is passed if a model has the ability to anticipate a steep peak in food prices based on the development of the conditioning factors.

Behavior Anomaly Test

In constructing and analyzing a System Dynamics model, one strives to have it behave like the real system under study. However, the analyst may detect anomalous features of the model's behavior which conflict with the behavior of the real system. Once the behavioral anomaly is traced to components of the model structure responsible for the anomaly, one often finds flaws in model assumptions. The test for recognizing behavioral anomalies is sporadically applied throughout the modeling process.

Family Member Test

A System Dynamics model often represents a family of social systems. Whenever possible, a model should be a general representation of the class of that systems to which the particular case belongs. One should ask if the model can generate the behavior in other instances of the same class. "The family-member test permits a repeat of the other tests of the model in the context of different special cases that fall within the general theory covered by the model. The general theory is embodied in the structure of the model. The special cases are embodied in the parameters. To make the test, one uses the particular member of the general family for picking parameter values. Then one examines the newly parameterized model in terms of the various model tests to see if the model has withstood transplantation to the special case" (Forrester and Senge 1980). The model should be calibrated so as to be applicable to the widest range of related systems. For the family member test, only the parameter values of the model are subject to alterations; changes in the model structure are part of the modified behavior test, as discussed in the preceding section.

Surprise Behavior Test

A surprising model behavior is a behavior that is not expected by the analysts. When such an unexpected behavior appears, the model analysts must first understand the causes of the unexpected behavior within the model. They then compare the behavior and its causes with those of the real system. In many cases, the surprising behavior turns out to be due to a formulation flaw in the model. However, if this procedure leads to the identification of behavior previously unrecognized in the real system, the confidence in the model's usefulness is strongly enhanced. Such a situation may signify a model-based identification of a counterintuitive behavior in a social system.

Turing Test

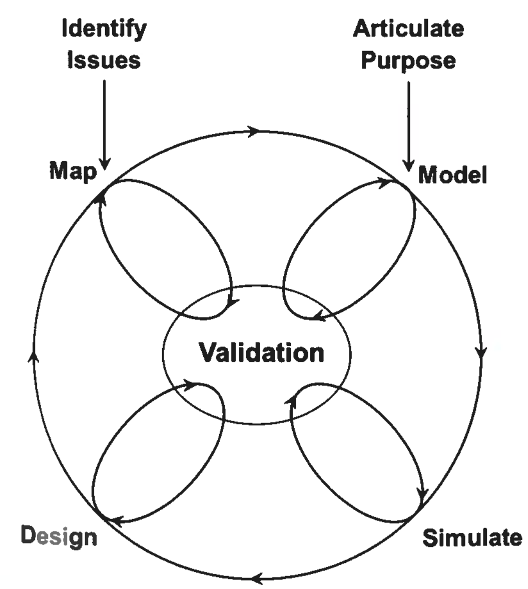
The Turing test is a qualitative test which uses the intuitive knowledge of system experts to evaluate model behavior. Experts are presented with a shuffled collection of real and simulated output behavior patterns. They are asked if they can distinguish between these two types of patterns. If they are unable to discern which pattern belongs to the real system and which to the simulation output, the Turing test is passed. Similar to the phase relationship test, the Turing test is powerful in its ability to indicate structural flaws but offers only little guidance for locating them in the model.

In another contribution, we have proposed heuristic principles for the choice of methods as a function of the complexity of the validation object, ranging from feedback loop, and combination of feedback loops, to whole model (Groesser and Schwaninger 2012).

Validation Process

The validation process pervades all phases of model building and reaches even beyond, into the phases of model implementation and use. The diagram in Fig. 4 visualizes the function of validation in the process of model building.

For the purpose of this contribution, validation is placed at the center of the scheme. From there it is dispersed through all steps of the modeling process, map (high-level modeling), model (building the formal model), simulate (scenarios, analysis), and design (of policies). We have limited the differentiation of these steps in order to highlight the structure of the process – a recursive structure drawn as a nested loop line. After the initial identification of issues and the articulation of model purpose, the simplified diagram denotes



System Dynamics Modeling: Validation for Quality Assurance, Fig. 4 Validation in the context of the System Dynamics modeling procedure

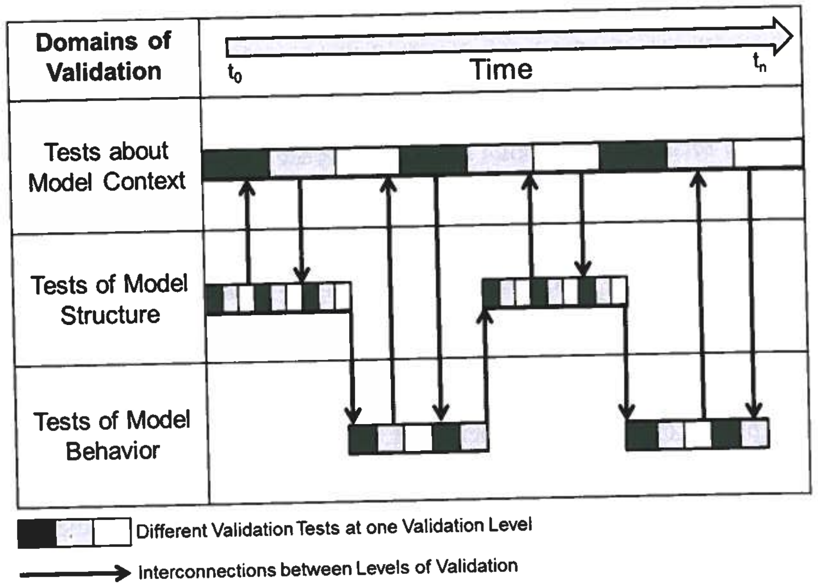
the four phases, of mapping to modeling to simulation and design. The small loops symbolize the microprocesses in which, for example, a model is submitted to validation, e.g., a direct structure test, which may lead to its modification (two small arrows). The larger loop illustrates more comprehensive processes. For example, an indirect structure test of the model is carried out, in which the behavior is tested by means of simulation. Or a policy test by simulation leads to implications for design (large loop), and the design is validated in detail thereafter (small loop).

Now, we should note that the process scheme reminds us of a further aspect which is quite fundamental. If the results of the model's operation, e.g., a "prediction," diverge from the results of a test, then either the model is wrong or the test is inadequate (Smith 2008: 168). This metaperspective lets us keep an eye on the adequacy of the tests: Is the logic of the test flawless? Are the data sources in order? (see "Adequacy of Methodology Test" in section "Validation Methods").

Model building is a process of knowledge creation, and model validation is an integral part of it. As the model is validated using the methods described in the former section, insights emerge, and a better understanding of the system under study keeps growing. But model building is also a construction of a reality in the minds of observers (von Glasersfeld 1991, von Foerster 1984) concerned with an issue. In this procedure, validation is supposed to be a "guarantor" for the realism of the model, a control function for preventing gross aberrations in individual and collective perceptions. Validation should encompass precautions against cognitive limitations and modeler blindness. The set of tests presented above is a system of partly heuristic and partly algorithmic devices for enhancing such provisions. A question not yet answered is how these tests should be ordered along the timeline. We have fleshed out three structural principles, which are illustrated in Fig. 5:

1. *Validation is a parallel process:* Validation at all three domains – context, structure, and behavior – is carried out in a synchronized

System Dynamics Modeling: Validation for Quality Assurance, Fig. 5 The interplay of validation activities



fashion. Contextual validation is perpetual, while the structural and behavioral validation are interrupted, from time to time by alternations.

2. *Parts of the validation process have a sequential structure:* This refers to the alternations between the components of structure and behavior validation. In principle, they occur alternately, with structural validation taking the lead and behavior validation following. After that, one might revert to structural validation again and so forth.
3. *Validation processes are polyrhythmic:* The length and accentuation of validation activities vary among the three levels. This fact is symbolized by the frequency of the vertical lines in the blocks of the chronogram.

A further important factor impinging on the validation process is the degree of resolution: micro, meso, or macro (as visualized in Fig. 1). The focus of validation is primarily on the micro-objects, the smallest building blocks of a model, for example, a stock or a subsystem containing a stock with its flows. One could call them metaphorically *atoms* or *molecules*. Each building block should be validated individually, before it is integrated into the overall model structure. The reason is that at this atomic level, dysfunctionalities or errors of thinking are discovered immediately, while at higher levels of resolution, the identification of structural flaws is more difficult and cumbersome. The same holds for the relation between modules (meso) and the whole model (macro). Before adding a module, it should have been validated in itself. This way, errors at the level of the whole system can be minimized, and also, it is very important to add, counterintuitive behavior of the model can be understood with more ease.

As far as details for the design of the validation process are concerned, along with the decision about when to stop the validation effort, we have dedicated a separate article to these issues (Groesser and Schwaninger 2012).

Until now we have treated what occurs in a validation process and how the process is structured. Finally, we raise the issue of who the actors are and why. In this context, we will concentrate on group processes in model validation.

Different observers associate diverse contents with a system, and they might even conceive the system distinctly, as far as its boundaries and structures are concerned. They might also succumb to erroneous inferences and therefore adhere to defective propositions. Consequently, error-correcting devices are needed. A powerful mechanism for this purpose is the practice of

model building and validation in groups. We have already reverted to that concept in respect to several of the methods discussed in the section on "Validation Methods," and now we will briefly expand on it.

Group model building (GMB) is a methodology to facilitate team learning with the help of SD (Vennix 1996). The methodology consists in a set of methods and instruments as well as heuristic principles. These are meant to facilitate the elicitation of knowledge, the negotiation of meanings, the creation of a shared understanding of a problem in a team, as well as the joint construction and validation of models. The process of GMB is essentially a dialogue in which different interpretations of the real system under study are exposed, transformed, aligned, and translated into the concepts and relationships which make up the model system. In other words that process is about both modeling and validation.

Given its transdisciplinary approach, GMB enables an integration of different perspectives into one shared image of the system in focus. GMB is an important provision for attaining higher model quality: It can broaden the available knowledge base, inhibit errors, and show itself to be a cohesive force in the quest for consensual model validation. The opportunity for validation inheres in the broad knowledge base normally available in a modeling group. Much of this knowledge can be leveraged for validation purposes. Most validation tests are carried out in cadence with the model-building activities. Often the tests become a task to be accomplished between the workshops. However, the members of the model-building group can, in principle, be made available for knowledge input into and monitoring of the validation activities.

A functioning GMB process requires a number of necessary elements (Phillips 2007): commitment of key players (e.g., attendance of workshops); impartial facilitation; on-the-spot modeling at conversational pace, with continuous display of the developing model; as well as an interactive and iterative group process.

Let us not forget that there are many situations in which one single person is in charge of building and validating a model. In these cases the modeler must constantly challenge his or her own position. Normally it is indicated that one should also call for external judgment in reviews, walkthroughs, and the like. The same holds for knowledge supply. One-person modelers can find a lot of material in the media, libraries, the Internet, etc., but it is also usually beneficial to find experienced persons from whom to elicit relevant knowledge or even persons who join the modeling and validation venture.

Finally, validation processes cannot go on forever, because costs would become prohibitive. At what point should the process be terminated? This question is important but not easy to be answered. The validation cessation threshold is not a fixed value; it depends on a variety of contingency factors such as a target group's experience with modeling, the relative importance/risk of decision, model size, costs of validation, the target group's expectations, data availability, data intensity, potential degree of validity of the model, and a modeler's level of expertise. An extensive treatment of this issue was presented elsewhere (Groesser and Schwaninger 2012).

Synopsis and Outlook

Models should be relevant for coping with the complexity of the real world. At the same time, the methods by which they are constructed must be rigorous; otherwise the quality of the model suffers. Rigor and relevance are not entirely dichotomous, but given resource constraints, they are in competition to a certain extent. Lack of rigor in building a model is often worse than limitations to the model's relevance. One may say, cum *grano salis*: Incomplete validation entails complete irrelevance. Modelers must find a way to ensure both rigor and relevance, as both are necessary conditions for achieving the model purpose. Neither alone is sufficient, but one may assume that, taken together, rigor and relevance are sufficient conditions. The relative importance of these two dimensions of model building may vary over time as a function of the model quality achieved. At the beginning, relevance might be more important, while at high levels of model accomplishment rigor might become prevalent.

Investing in high model quality is indeed both worthwhile and imperative. It is impressive to register the fact that model validation has achieved higher levels of rigor not only in the academic ambit but also in the world of affairs: According to Coyle and Exelby, the need for orientating decisions about "real-world" affairs has also fueled strong efforts among commercial modelers and consultants for ensuring model validity (Coyle and Exelby 2000).

We have discussed two essential aspects of model validation, the epistemological foundations and methodological procedures for ensuring model validity. The main conclusion we have reached on epistemology is that crude positivism has been superseded by newer philosophical orientations that provide guidance for an adequate concept of validation in System Dynamics. Validation has been defined as a rich and well-defined process by which the confidence in a model is gradually enhanced. Validity, then, is always a matter of degree, never an absolute property.

Well defined here is not meant in the sense of a rigid algorithm, but as the rigorous application of a battery of validation methods which we have described in some detail.

Future research should account for the importance or priority of the different tests as perceived by practitioners and academics. This, of course, is relevant since resources for validation – i.e., time, monetary resources, expert knowledge, and appropriate data – are scarce (Groesser and Schwaninger 2012). We have included a number of new validation tests by which modelers' understanding of the relevant context can be scrutinized. These additional tests are rightly supposed to prevent wrong methodological choices. They should also trigger innovative approaches to the issues under study and foster the ability to think in terms of contingencies. Finally, they should liberate modelers from tunnel vision and open avenues to creativity. The imperative here is to cultivate a "sense of the possible" (Robert Musil's *Möglichkeitssinn*) and a skepticism against the supposedly impossible (see also Taleb 2007).

Simulation based on formal dynamic models is likely to become ever more important for both private and public organizations. It will continue to support managers at all levels in decision-making and policy design. The more that models are relied upon, the greater the importance of their high quality. Therefore, model validation is one of the big issues lying ahead in System Dynamics modeling.

Appendix: Overview of the Tests Described in This Entry

- Tests of Model-Related Context
  - Test of Model Framing
  - Issue Identification Test
  - Adequacy of Methodology Test
  - System Configuration Test
  - System Improvement Test
- Tests of Model Structure
  - Direct Structure Tests
    - Structure Examination Test
    - Parameter Examination Test
    - Direct Extreme Condition Test
    - Boundary Adequacy Structure Test
    - Dimensional Consistency Test
  - Indirect Structure Tests
    - Mass-Balance Check
    - Indirect Extreme Condition Test
    - Behavior Sensitivity Test
    - Integration Error Test
    - Boundary Adequacy Behavior Test/Boundary Adequacy Policy Test
    - Loop Dominance Test
- Tests of Model Behavior
  - Behavior Reproduction Tests
    - Symptom Generation Test
    - Frequency Generation and Phase Relationship Test
    - Modified Behavior Test
    - Multiple Modes Test
    - Behavior Characteristic Test
  - Behavior Anticipation Tests
    - Pattern Anticipation Test
    - Event Anticipation Test
  - Behavior Anomaly Test
  - Family Member Test
  - Surprise Behavior Test
  - Turing Test

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Optimization of System Dynamics Models

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Article Outline

Glossary

Econometrics a statistical approach to economic modelling in which all the parameters in the structural equations are estimated according to a "best fit" to historical data.

Maximum likelihood a statistical concept which underpins calibration optimization and which generates the most likely parameter values; it is equivalent to the parameter set which minimizes the chi-square value.

Objective function see **Payoff** below.

Optimization the process of improving a model's results in terms of either an aspect of its performance or by calibrating it to fit reported time series data.

Payoff a formula which expresses the objective, say, maximization of profits, minimization of costs, or minimization of the differences between a model variable and historical data on that variable.

Zero-one parameter a parameter which is used as a multiplier in a policy equation and serves the effect of bringing in or removing a particular influence in determining the optimal policy.

Definition of the Subject and Its Importance

The term "optimization" when related to system dynamics (SD) models has a special significance. It relates to the mechanism used to improve the model vis-à-vis a criterion. This collapses into two fundamentally different intentions. Firstly one may wish to improve the model in terms of its performance. For instance, it may be desired to minimize overall costs of inventory while still offering a satisfactory level of service to the downstream customer. So the criterion here is cost, and this would be minimized after searching the parameter space related to service level. The direction of need may be reversed, and maximization may be desired as, for instance, if one had a model of a firm and wished to maximize profit subject to an acceptable level of payroll and advertising costs. Here the parameter space being explored would involve both payroll and advertising parameters. This type of optimization might be described generically as *policy optimization*.

Optimization of performance is also the *raison d'etre* of other management science tools, most notably mathematical programming. But such tools are usually static: they offer the "optimum" resource allocation given a set of constraints and a performance function to either maximize or minimize. These models normally relate to a single time point and may then need to be rerun on a weekly or monthly basis to determine a new optimal resource allocation. In addition, these models are often linear (certainly so in the case of linear

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