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Methodological Problems in the Formulation and Validation of System Dynamics Models Incorporating Soft Variables

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Abstract
While formulating and then analyzing a system dynamics model that incorporates soft, qualitative variables, problems are encountered. First most of the variables of this kind are measured using a quasi-quantitative framework. The question of reliability and validity of such measurement needs to be addressed. Second, the causal relationships among the variables would have to be ascertained in a way that takes into consideration such a measurement approach. Further, there is the critical question of validating such a system dynamics model. The paper attempts to probe into the problems of developing system dynamics models that incorporate soft variables, and critically examines the model validation exercise in system dynamics in this context. It argues for enriching the methodology of system dynamics by establishing an interface with the methodology of structural equation modelling that would help address the issues of reliability and validity of the measures and the formulation and subsequent validity of the system dynamics model.

Keywords
System dynamics, causality, reliability, validity, structural equation modelling.

INTRODUCTION

The debate over methodological issues that concern system dynamics (SD) paradigm and the shortcomings of the traditional approach to system dynamics problem-solving has been increasingly veering towards the question of interfacing the field of system dynamics with various soft systems methodologies. Lane (1994) has argued that there is much benefit to be derived from a dialogue between the practitioners of system dynamics and those of soft OR (operations research). A great deal of concern has been expressed because of the isolation of system dynamics from other techniques and because of methodological issues in system dynamics that the fields of soft OR and other problem-solving methodologies have already begun to address.

It may be mentioned that at the time when system dynamics was being founded, there was a conscious separation of it from OR. Forrester (1968a) had recognized the need for the practice of management to evolve from being an art. However, he was unconvinced about the effectiveness of the 'science' of management (that is, OR) as it was then constituted. This 'science' concept of traditional OR has also been critically commented upon by Ackoff (1979, 1987). He has criticized objectivity as an impossible goal in a specific situation although he has admitted that it could be a systemic property of scientific endeavour as a whole. He has subsequently rejected the concept of optimality as being impractical because of the exclusion of esthetics and the emphasis on the utility of ends to the exclusion of means and irrelevant because of the rate of change in social and organizational systems. Advocating systems thinking and practice as against OR, he has recently commented (Ackoff, 2001, p. 346), 'Systems thinking and practice are what OR could and should have become. It focuses on the performance of wholes rather than parts…'.

According to Greene (1994), the questions of the theoretical bases, or lack thereof, of system dynamics practice and of the relationships of system dynamics to other system theories have had limited acknowledgement in the literature. Awareness of the strengths and weaknesses of the different systems methodologies, and of the social consequences of using each type, leads to the possibility of employing them in a pluralist or complementary manner - each used when and where it is the most appropriate (Jackson, 1995). Andersen and Rohrbaugh (1992) have described a demonstration experiment that was designed to link a simulation model with formal models of judgment. The simulation-modelling technique chosen was system dynamics, and the judgment-modelling approach selected was social judgment analysis. Models derived from social judgment analysis were attached to a system dynamics model to create a new objective function sector. Framinan-Torres and Ruiz-Usano (1997) have attempted to model neural networks using system dynamics. Kennedy (1997), and Savicic and Kennedy (1997) have tried to integrate spreadsheets into system dynamics models. Forrester (1994) has emphasized that soft OR usually lacks the discipline of explicit model creation and simulation and so relies on subjective use of unreliable intuition for evaluating the complex structures that emerge from the initial description of the real system. However, he has shown agreement that soft OR, with emphasis on elucidating information from real world participants, should contribute useful insights to system dynamics.

Greene (1994) has further argued that there are a number of real world behaviours of complex living systems that classical system dynamics cannot completely explain. He has argued that SD should be integrated with dissipative-structure theory, synergistics, catastrophe theory, field theory and chaos theory in order better to explain and to predict evolution, the different kinds of stability and instability, structural change and structural constancy, the different kinds of equilibrium situations, bifurcation, the emergence of collective behaviour, and the qualitative meaning of information. Techniques like the balanced scorecards (Kaplan and Norton, 1996) are essentially linear, open loop approaches but these have their own usefulness. Barlas (1995) has considered the relationships between system dynamics and the methodologies and approaches like chaos, simulation gaming, soft systems methodology and systems thinking and has commented that there are still various issues in these relationships that need to be clarified. Lane and Oliva (1994) have argued for a synthesis of SD and soft systems methodology (SSM). In their paper, Rios and Schwaninger (1996) have shown that a combination of system dynamics and the methodology of network thinking (MNT) developed at the University of St. Gallen could help overcome some of the limitations of both methodologies, and realize substantial synergy between them. They have called this synthesizing methodology 'Integrative Systems Modelling'. Kummer and Schlange (1997) have presented a set of tools that contribute to the critical issue of linking the stages of SD and qualitative modeling approaches such as MNT and sensitivity model (SM). Richardson (1996) while commenting upon the problems for the future of system dynamics has stated that the field is experiencing the increasing use of qualitative tools - systems archetypes, word-and-arrow diagrams under various labels (casual-loop diagrams, influence diagrams, cognitive maps), and other approaches and techniques that fall under the general rubric of qualitative systems thinking.

All said and done, there are certain distinct advantages of using the SD methodology for testing social theory. As has been pointed out by Jacobsen (1984), first, it is possible to handle many variables simultaneously, and study their fluctuations over time. Secondly, we can take account of multiple feed back loops in the system under investigation and study their mutual influences, again, over time. However, the traditional approach of system dynamics problem solving faces a roadblock when we attempt to model social systems that incorporate soft variables whose measurement is beset with the problems of systematic and random measurement errors. Further, causal linkages among these soft variables are not easily ascertained. Thus, there are critical problems associated with such a modelling exercise both at the model formulation stage as well as at the model validation stage. Even if the model is formulated on the basis of prior knowledge and assumptions, results of past empirical research, and statistical deductions, yet the model cannot be validated following the standard procedures for system dynamics model validation as the presumed causal linkages among the soft variables incorporated in it cannot be verified.

It may be pointed out that in this context that causality or causal linkages are central to the paradigm of system dynamics. In fact, adopting a rigorous approach to systems descriptions in terms of influence or causal loop diagrams has been advocated by Wolstenholme and Coyle (1983), Coyle (1996), Coyle and Alexander (1996) and Wolstenholme (1999). Commenting on such type of works, Coyle (2000, p. 226) has written, 'In none of this work was it stated or implied that dynamic behaviour can reliably be inferred from a complex diagram; it has simply been argued that describing a system is, in itself, a useful thing to do and may lead to better understanding of the problem in question. It has, on the other hand, been implied that, *in some cases*, quantification might be fraught with so many uncertainties that the model's outputs could be so misleading that the policy inferences drawn from them might be illusory' (emphasis original). He has restated with further reasoning in a rejoinder (Coyle, 2001) to a response to his earlier paper by Homer and Oliva (2001) his concerns about the reliability of conclusions drawn from simulations when there are soft variables in the model.

In the light of the above discussion, the primary argument of the paper is to probe into the problems of developing system dynamics models that incorporate soft variables, and to critically examine the model validation exercise in system dynamics in this context.

The paper puts forward an argument for enriching the methodology of system dynamics by establishing an interface with the methodology of structural equation modelling that would not only enable it to take care of the systematic and random measurement errors encountered while these variables are measured in a quasi-quantitative framework, but would also prove helpful in ascertaining causal linkages among these soft variables. Causal relationships represent the most fundamental understanding of the process under study and such knowledge is relatively invariant through time and space (Duncan, 1975). The central theme of structural equation modeling is establishing causal relationships among latent or conceptual variables. Such causal linkages could then be appropriately incorporated into the system dynamics model and help in its formulation where, as argued by Homer and Oliva (2001), simulation can add value beyond mapping alone in most cases. This exercise could serve as a first step towards validating such a system dynamics model.

SYSTEM DYNAMICS MODELLING WITH SOFT VARIABLES

Modelling of inanimate systems is relatively easy. Modelling of social systems is quite complicated. Modelling of abstractions like decision network and information flows, and also of human competencies and motivation, is a matter of immense attractions and endless possibilities. System dynamics models have often been criticized with respect to the measurement of data and parameter estimation involved in the models. Nordhus (1973) has labeled the world dynamics model as measurements without data. Legasto and Maciariello (1980) have reviewed a number of criticisms on SD models. The criticisms pertain to problem definition, level of aggregation, parameter estimation and inference of results. Another important criticism comes from Cole (1979) who has argued that SD models used for analyzing social systems are not explicit about the social theory that is employed for analysis.

Conventional methods and models are based on hard (quantitative, cardinally-measured) information. The problems are different in the analysis of soft, qualitative or categorically measured data. Soft modelling methodologies aim at taking into account the limitations caused by measuring variables on a non-metric scale, and try to avoid the use of non-permissible numerical operations on qualitative variables. The importance of this had been recognized way back by van Gigch (1974). He had stated, and we quote here, 'The outputs of "hard" systems are for the most part tangible and "quantity-like" as opposed to those of soft systems which may be characterized by a greater proportion of "quality-like" outputs. For this reason it is expected that the outputs of soft systems will be measurable along weaker scales of measurement than the outputs of hard systems. This is not necessarily a drawback. It means that special methods will have to be devised to cope with that limitation' (p. 169).

While developing system dynamics models incorporating soft variables, researchers often encounter several problems. These problems need to be resolved if the model is to show any meaningful result. To begin with, there is the problem of measurement of these variables. Mutec (1994) has developed SD models while investigating the dynamics of employee participation. In these models, he has used concepts like motivation and dissatisfaction as rate variables. But nowhere he has mentioned how these and similar other variables have been measured.

Coyle (2000) has referred to the problems involved in the quantification of soft variables in a system dynamics model that is often a multiplier variable with values ranging from 0 to an upper limit that may exceed 1 and having a non-linear relationship with the parent variable that it is supposed to represent. The nature of such a non-linear behaviour is a cause for uncertainty. Further, he has commented that the problems become more acute when several multipliers are used and the often used assumption that the multipliers are multiplicative in nature might be off the mark a long way. A study of the system dynamics model of work climate of an R&D laboratory, developed by the authors (Roy and Mohapatra, 1994), bears this out further. The causal relationships in the particular system dynamics model were largely derived from correlations, regression analysis, cluster analysis and multiple classification analysis. The problem, however, is that in none of the methods of analysis mentioned above, causality can be inferred or verified. It is possible to produce a correlation model giving good fit but implausible causal relationships (Lane, 1995). Mass and Senge (1978) have shown that regression can fail to infer from a data set the existence of a feedback link present in the model that generated the set.

MODEL VALIDATION IN SYSTEM DYNAMICS: ISSUES AND PERSPECTIVES

Model validation is an important aspect of any model-based methodology in general and system dynamics in particular. Validity of the results of a given study is crucially dependent on the validity of the model. Model validation may be defined as 'establishing confidence in the usefulness of a model with respect to its purpose' (Barlas, 1996, p. 184). According to Coyle (1996), a valid model means 'well suited to a purpose and soundly constructed' (p. 12). According to Greenberger et al. (1976), no model could be thoroughly validated. A model should be useful, illuminating, and should inspire confidence. They have commented that these are perhaps more apt descriptors applying to models than its validity. According to Forrester (1968b), it is pointless to discuss validation 'without reference to the particular situation' (p. 616). Coyle and Exelby (2000) have emphasized that there is no such thing as absolute validity, only a degree of confidence which becomes greater as more and more tests are performed. They have stressed that, one, validation means ensuring that the model's structure and assumptions meet the purpose for which it is intended; and second, verification means ensuring that its equations are technically correct.

System dynamics models claim to be causal ones. According to Lane (1995), SD models produce insight, not foresight. Moreover, an SD model constitutes an assembly of causal hypothesis about relationships between variables supporting time-evolutionary behaviour. In fact, Randers (2000) has commented that one of the basic tools of system dynamics that have stood the test of time is a focus on the basic causal structure. Even in some cases, as suggested by Coyle (1998) and Wolstenholme (1999), a model can be entirely qualitative, consisting only of an influence diagram. Coyle (2001), referring to the value of an influence diagram or a causal loop diagram for system dynamics, has stated that , among other benefits, the study of a well-drawn influence diagram portrays complexity and shows patterns of feedback and seeing those can be helpful, even though dynamics cannot be predicted from it. Moreover, it can serve as the basis for a simulation. A system dynamics model is refuted if a critic can show that a model equation conflicts with a known causality, even if the output behaviour of the model matches the observed problem behaviour. In system dynamics, 'validity' means the validity of the internal structure of the model, not its output behaviour (Barlas, 1994).

According to the traditional reductionist/logical empiricist philosophy, a valid model is an objective representation of a real system. According to this philosophy, validity is seen as a matter of accuracy, rather than its usefulness. The comparatively recent relativist/holistic philosophy has argued for the model as one of the many possible ways of describing a real situation. Barlas and Carpenter (1990), supporting this viewpoint, have suggested that model validation cannot be entirely objective, quantitative and formal. Since validity means usefulness with respect to a purpose, model validation has to have subjective, informal and qualitative components. Barlas (1996) has emphasized that the issue of validation of a system dynamics model is much more complicated than that of a black-box model, because judging the validity of the internal structure of a model is very problematic, both philosophically and technically. According to him, it is philosophically difficult, because the problem is directly related to the unresolved philosophical issue of verifying the truth of a (scientific) statement. And the problem is technically difficult because there are no established formal tests (such as statistical hypothesis tests) that one can use in deciding if the structure of a given model is close enough to the 'real' structure.

Forester's (1961) and Forrester and Senge's (1980) works are still the backbone of today's SD model validation discourse. Wolstenholme (1990) and Mohapatra et al. (1994) have restated the Forrester and Senge tests. Other works considering validation in detail include those of Coyle (1977, 1996). They have given examples of direct structure tests as structure and parameter verification test, direct extreme-conditions test and dimensional consistency test. Accordingly, structure verification test means comparing the structure of the model against the structure of the real system, or as Barlas (1994) has pointed out, this could also be carried out as a theoretical structure test, by comparing the model structures against knowledge available in the literature. Parameter verification test means evaluating the constant parameters against knowledge of the real system, both conceptually and numerically. Richardson and Pugh (1981) have also emphasized the importance of system structure.

Validation as an issue of research

Validation as an issue of research and debate has largely eluded the practitioners of system dynamics. Barlas (1996) has pointed out that a survey has indicated that little effort has been devoted by the system dynamics community to model validity and validation. According to his study, only three of all the papers published in *System Dynamics Review* (between 1985 and 1995) deal with model validity and validation. The question of validity assumes critical concern for models incorporating soft variables. The primary concern in such cases is the validity of the structure of the model. Barlas (1996) after an overview of the philosophical aspects of model validation has shown that (p. 188):

1. Validity of a system dynamics model primarily means validity of its internal structure.
2. The recent relativist/holistic philosophy has argued that validation of the internal structure cannot be made entirely objective, formal and quantitative (in the sense that even scientific theory confirmation has informal and subjective aspects).

However, he is quick to point out that relativist/holistic philosophy does not reject the role of formal/quantitative tests in model validation, but that these tests provide crucial inputs to the larger validation process, which is gradual, semi-formal and conversational.

Forrester and Senge (1980) have also displayed such a concern while debating upon the nature of validity in system dynamics models. They have stated, and we quote here, 'We take the view that the ultimate objective of validation in system dynamics is transferred confidence in a model's soundness and usefulness as a policy tool. The notion of validity as equivalent to confidence conflicts with the view which many seem to hold which equates validity with absolute truth. We believe confidence is the proper criterion because there can be no proof of the absolute correctness with which a model represents reality. There is no method for proving a model to be correct…. Validity is also relative in the sense that it can only be properly assessed relative to a particular purpose' (p. 211). It should be noted that the notion of a model as an aid to learning about the behaviour of complex, non-linear management systems is a valid one; models cannot be devised which will provide 'answers' to what can be quite opaque 'issues' at the strategic level (Morecroft, 1992; deGeus, 1992).

In hard systems, models are representative of the real world. Landry et al. (1983) while discussing model validation in operations research have referred to the context in which the model would be used - by whom, for what purpose and in what mode, predictive or prescriptive? Answers to these questions in the particular context would determine what validation techniques would be regarded as appropriate. On the other hand, in problem structuring methodologies like soft systems methodology, SSM (Checkland, 1979; Checkland, 1981; Checkland and Scholes, 1990; Checkland et al., 1990), model validation is no longer a paramount issue since in SSM the concept of a model as surrogate for a part of reality is itself abandoned (Checkland, 1995). In such a situation where a model is treated as 'epistemological device', the question of validity revolves around the question of whether the model is relevant and whether it is competently built. The question of technical validation is faced by asking whether a pairing of root definition and model is defensible (Checkland, 1995). Such a methodology makes no assumptions about the nature of the world apart from the fact that it is considered to be complex. The approach which assumes the world to be systemic is hard and the one which assumes that the process of inquiry can be systematic is soft. The real distinction between the two is marked by the shift of assumed systemicity, from the world to the process of enquiry into the world (Checkland, 1983).

Clearly, our approach towards soft systems modelling is quite different from the methodological thrust of SSM and other problem structure methodologies. As mentioned earlier, SD itself has moved away from the hard systems paradigm with the relativist/holistic philosophy of validation. Secondly, in SSM the problem situation could be ill-structured and messy whereas the variables in the model need not be so. These variables in the model could be perfectly measurable and quantifiable. Moreover, in SSM we are not looking to develop a causal model which could then form the basis of a system dynamics model SD models try to offer explanation and understanding, not only forecasting and control (Vazquez et al., 1996). Lane (1995) has differentiated between the formulations of SD as he has defined them – ardent SD which aims to access the strong simulation theory of SD but cannot hope to perform too well on the cultural factors and so there is a reduction of process effectiveness resulting from low targets on conceptual and data validities; abridged (qualitative) SD which may attempt a richer social intervention but at the expense of low analytical quality, much in common with soft OR processes but lacking in the provision of simulation models for the conduct of meaningful experiments; and abridged (discursive) SD. He has then argued for an extended SD to overcome these limitations. He has emphasized that achieving conceptual validity requires a careful management of the social 'mess' of problem solving. The 'real world' here is often fuzzy and messy. While soft OR compensates for one of the major flaws in hard systems thinking by accepting subjectivity, it does not address the others. The insights that cybernetics, for example, can bring to the understanding and management of complexity are ignored (Jackson, 1994).

Validating models with soft relationships

An important characteristic of system dynamics modeling is the use of soft as well as hard relationships. SD provides a balanced perspective to handle both hard and soft system-based problems. However, a closer look into the question of validation of a system dynamics model that incorporates soft variables brings out the criticality of the issues involved and of the problems encountered in adopting the standard procedures for validation of SD models for validating such a model. Richardson (1996) has commented that the field of system dynamics needs to achieve greater consensus concerning what types of confidence-building and validation procedures and tests are more appropriate in what types of decision environments. In his opinion, there is a need to accumulate wisdom about the conditions under which various types of tests and procedures appear to be most appropriate.

As has been pointed out earlier, the latent, unobserved and conceptual soft variables incorporated in a system dynamics model cannot be measured directly and objectively. The measured values of these variables are derived from observed indicators. Such a measurement scheme is referred to as quasi-quantitative measurement. Subjective measures are influenced by systematic and random *measurement errors. The structure of relationships among these variables is often unclear and the causal linkages cannot be ascertained. Hence, it is essential that the reliability and the construct validity of these measures of soft variables are assessed before the values of these variables are used in empirical studies. This would also help minimize judgmental scaling errors often encountered in such modelling initiatives. Further, the causal linkages among the soft variables thus measured would have to be ascertained keeping in mind the measurement errors inherent within. It is, therefore, clear that the validity of such a system dynamics model is dependent critically upon the validity and reliability of such quasi-quantitative measurement. An exercise of this sort could then help formulate the system dynamics model based on these causal linkages and could also serve as a pre-validation exercise for the proposed model.

QUASI-QUANTITATIVE MEASUREMENT: VALIDITY AND RELIABILITY

By validity we mean the ability of a technical instrument to provide data related to what we assume to be real in that particular research context. Validity is concerned with whether a variable measures what it is supposed to measure. Content validity is a qualitative type of validity where the domain of a concept is made clear and the analyst judges whether the measures fully represent the domain. Criterion validity is the de gree of correspondence between a measure and a criterion variable, usually measured by their correlation (Bollen, 1989). Validity is an epistemological issue.

Construct validity is the extent to which an observation measures the concept it purports to measure. A widely accepted procedure for construct validation in social sciences is the method of multi-method multi-mode (MTMM) matrix (Campbell and Fiske, 1959) whereby the validity of a construct is inferred through the pattern and magnitude of covariations among the multiple measures of a construct and comparison of these measures of a construct with the measures of one or more other constructs. They have proposed two broad criteria for construct validation: convergent validity and discriminate validity.

Convergent validity refers to the extent to which multiple measures of a construct agree with one another. If two or more measures are true indicators of a concept, then they should necessarily be highly correlated. This assumption is consistent with the 'reflective measurement model'. Failure to find high covariation among multiple measures of a construct would imply that either the measures are poor and/or the construct and the measures do not correspond with each other (Bagozzi and Phillips, 1980).

Discriminate validity is the degree to which measures of different constructs are distinct from each other. This means that measures of different constructs should share little common variance (in a relative sense).

Reliability refers to the ability to achieve identical or similar outputs from the work of different researchers and by the repeated use of the technical instruments for data collection. Reliability is a methodological issue. Reliability could be conceived as a property of the instrument and of the observer that uses it to observe many times the state of an object on a property. It can be considered as the inverse of the variance of all the observations pertinent to the same state. The higher this variance is, the less reliable the couple observer-instrument.

Both the validity and the reliability of the statistical techniques used in data processing procedures constitute an important issue concerning the validity of inferences. A critical analysis developed on the data processing techniques takes into account both their correct application and their ability to provide information from which to draw inferences with a testable relationship of correspondence between a piece of information and an inferred sentence.

STRUCTURAL EQUATION MODELLING: THE LISREL APPROACH

Structural equation modeling (Joreskog, 1969, 1973, 1978; Browne, 1977; Sorbom and Joreskog, 1978; Bollen, 1989, 1990; Fox, 1984; Long, 1981, 1983; Joreskog and Sorbom, 1984, 1989, 1993; Saris and Stronkhorst, 1984, Hayduk, 1987) is a statistical methodology that takes a hypothesis-testing (i.e., confirmatory) approach to the multivariate analysis of a statistical theory bearing on some phenomenon. Typically this theory represents causal processes that generate observations on multiple variables. The term structural equation modeling conveys two important aspects of the procedure: (a) that the causal processes under study are represented by a series of structural equations, and (b) that these structural equations can be modelled pictorially to enable a clearer conceptualization of the theory under study. LISREL (Linear Structural Relations) is a program for estimating structural equation models. LISREL produces a full information maximum likelihood solution (FIML), which makes use of all information in the data about each parameter in generating its estimates (Joreskog, 1969, 1978). If a concept is directly caused or influenced by any of the other concepts, it is classified as endogenous. If a concept always acts as a cause and never as effect, then it is exogenous, and functions in the values of these concepts are not to be explained by this model (though they may be used to explain fluctuations in the values of the endogenous concepts). Thus, the direct causal effects that are of interest are located (Hayduk, 1987).

Structural equation modeling is a statistical methodology that takes a hypothesis testing (i.e. confirmatory) approach to the multivariate analysis of a structural theory bearing on some phenomenon. Typically, this theory represents ‘causal’ processes that generate observations on multiple variables. The term structural equation modelling conveys two important aspects of the procedure: (a) that the causal processes under study are represented by a series of structural equations, and (b) that these structural relations can be modelled pictorially to enable a clearer conceptualization of the theory under study. The central theme of structural equation modelling is to ablish casual relationships among the latent variables.

LISREL 7.16 program (Joreskog and Sorbom, 1989) has been used in the study reported in the present paper. Ordinary least squares impose restrictions on correlated errors, which the LISREL 7.16 model does not impose. Thus, models with independent variables that can be fixed can be considered to directly influence the dependent variables (Howard and Frink, 1996). LISREL is a computer program for estimating general linear structural equation models with the specific advantage of allowing for unmeasured hypothetical constructs or latent variables, each of which may be measured by several observed indicators. The method allows for differentiation between errors in equations (disturbances), and errors in the observed variables (measurement errors) and yields estimates for both. Thus, in LISREL, measurement concerns become integrated with model development, estimation, evaluation and interpretation (Bohrnstedt, 1983).

LISREL 7.16 also allows for the examination of the fit of the model. A test statistic (t) indicates significance of the specific coefficients, whereas goodness-of-fit (GFI) and root mean square residual (RMSR) can also be used simultaneously (La Du and Tanaka, 1989). GFI is the preferred statistic in assessing the fit of the path model to the data, in that it measures the relative amount of variance and covariance accounted for by the model. The value of GFI ranges from 0 (poor fit) to 1 (perfect fit). RMSR is a measure of the average variance unaccounted for by the model. The basic LISREL model amounts to a general procedure for doing structural equation modeling (path analysis) in a way that preserves the distinction between concepts and indicators.

AN EXAMPLE OF THIS APPROACH

In a particular study, 602 research units were identified in 32 laboratories of the Council of Scientific and Industrial Research (CSIR), India. A research unit (RU) is operationally defined as a unit that has the following characteristics:

1. It has at least one project in the unit.
2. It has a total expected life span of at least one year.
3. It is comprised of at least three core members, among whom there is one scientist who is the head of the unit. A core member is an individual researcher or a technician who devotes at least eight hours per week to the work of the research unit and who has direct or indirect communication with the head of the unit at least once in a month.

After a two-stage random sampling design was adopted for data collection, usable data were obtained from 236 research units. In the second stage, for each sampled research unit, samples of core members were selected at random subject to a maximum of three scientists/engineers, and three technicians. The data were collected through a set of standardized questionnaires administered to the head of the unit, the staff scientists, engineers and technicians of the research unit and to the external evaluators. There were in all 834 respondents; of these 236 were heads, and the rest scientists, engineers and technicians.

The data were used to develop two structural equation models involving latent variables conceptualizing various dimensions of organizational climate and the measures of effectiveness of research units in CSIR laboratories.

Internal consistency of the indices for all the concepts were assessed using Cronbach alpha coefficient (Cronbach, 1951) which ranges from 0, no reliability to 1, perfect reliability (Lord and Novick, 1968), before the structural models were developed using these variables. From the initial list of the concepts, only those concepts were considered for further analysis whose Cronbach alpha coefficients were more than 0.5. The broad results of the study including the LISREL fit indices (root mean square residual (RMSR) and the goodness-of-fit index (GFI)), the parameter values of the structural coefficients, and squared multiple correlations (R^2) and the coefficient of determination for the structural equations of the models have been presented in an earlier paper by Roy and Mohapatra (2000).

As an illustration of the usefulness of structural equation modelling for systems incorporating soft variables, a causal loop diagram derived from the second structural equation model developed in the above-mentioned study is presented here. The second structural model involves the following exogenous variables - leadership quality and supervisor contact effectiveness, and the following endogenous variables - innovative ethos, conflict, communication, research planning quality, R&D effectiveness, and recognition.

A positive causal loop is observed among the endogenous concepts of innovative ethos, communication, research planning quality and R&D effectiveness. This causal loop is shown in Fig. 1. This is a self-reinforcing loop where an increase in the value of a variable, say the levels of communication within the research unit would trigger an exponential rise in the values of the variables. Conversely, a decrease in the levels of communication would trigger an exponential fall in the values of the variables. However, it may be noted that the suggested dynamic behaviour will occur if all the other variables remain constant. Moreover, it may be noted that R&D effectiveness has not been adequately explained by the model as given by the values of the squared multiple correlations for the structural equation (Roy and Mohapatra, 2000) and one should adopt caution while explaining the loop.

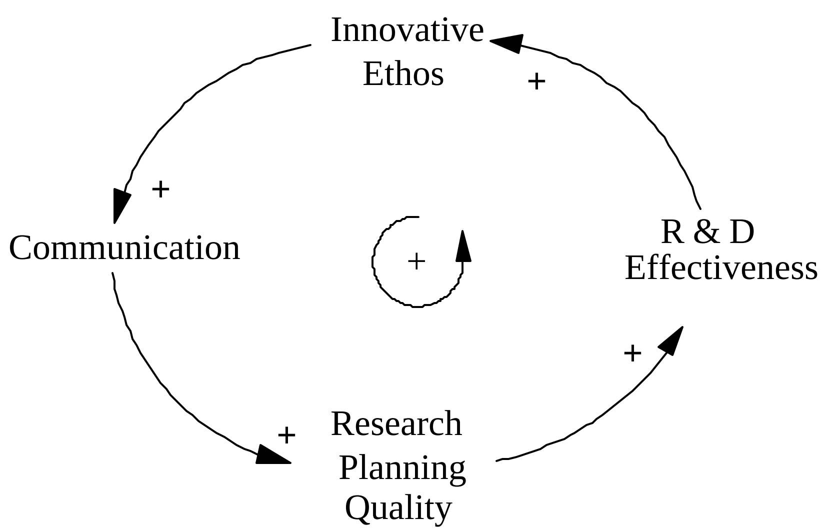

Fig. 1: R & D Effectiveness Causal Loop

CONCLUSIONS

It has been emphasized that the subjective measures of soft variables are influenced by systematic and random measurement errors. Hence, it is essential that their reliability and construct validity should be assessed before these are used in empirical studies. The validity of the system dynamics models incorporating soft variables is thus dependent upon the construct validity and reliability of such quasi-quantitative measures. Moreover, the relationships among the latent variables or concepts developed from the observed variables have to be ascertained in a way that takes into account this quasi-quantitative measurement approach. There are, therefore, inherent problems that are encountered while such system dynamics models are formulated and later while these models are validated for arriving at any meaningful inference and insight. The core methodology of system dynamics would, therefore, be greatly enriched by interfacing with methodologies like the structural equation modeling that could specifically be helpful in addressing such issues.

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