To Main Proceedings Document

Causality and Validation of System Dynamics Models Incorporating Soft Variables: Establishing an Interface with Structural Equation Modelling

Santanu Roy
National Institute of Science Technology and Development Studies
Dr. K.S. Krishnan Marg, Pusa,
New Delhi 110 012, India
e-mail: rsan58@yahoo.co.uk fax: 0091 11 575 4640/ 623 7401
phone: 0091 11 726 8593 ®/ 644 6557 ®

Pratap K.J. Mohapatra
Department of Industrial Engineering and Management
Indian Institute of Technology
Kharagpur 721 302, India
e-mail: pratap@hijli.iitkgp.ernet.in; **fax: 0091 3222 55303**

Abstract

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. Social scientists have been more and more concerned with measuring qualities in order to grapple with complex configurations and the ambiguities inherent in human perceptions and behaviour. The authors had earlier attempted to model the work climate of an R&D laboratory using the system dynamics (SD) framework. Problems occur at two stages in developing such a system dynamics model incorporating soft variables. First most of the variables encountered in such systems are measure using a quasi-quantitative framework. The question of reliability and validity of such measurement would have to be addressed. Second, the causal relationships among the variables would have to be ascertained in a way that takes into consideration this quasi-quantitative measurement approach. Reliability refers to the stability of replicated measurements. Construct validity refers to whether the measure really measures what it is supposed to measure, as opposed to measuring some similar yet conceptually distinct variable. Causality or causal linkages are central to the paradigm of system dynamics. The causal relationships in the above-mentioned system dynamics model were largely derived from correlations, regression analysis, cluster analysis and multiple classification analysis. But in all these methods of analysis, causality cannot be inferred or verified. Further, there is the critical question of validating such a system dynamics model. Our approach towards soft systems modelling is quite apart from the methodological thrust of soft systems methodology (SSM) and other problem structure methodologies. For one, SD itself has moved away from the hard system 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. The central theme of structural equation modelling is the establishments of causal relationships among latent variables taking into consideration the reliability and validity of quasi-quantitative measurement of such variables. It is, therefore, argued that establishing an interface between system dynamics and structural equation modelling could be appropriate to address the problem of establishing causality in and validation of a system dynamics model incorporating soft variables. Data from a sample of 236 research units in the laboratories under the Council

of Scientific and Industrial Research (CSIR), India have been used to develop two structural equation models. These models help in probing into the causal relationships among the factors of work climate and the measures of effectiveness of research units in CSIR laboratories.

1. System Dynamics, Hard and Soft Systems and the Question of an Interface

Interfacing system dynamics (SD) with various soft systems methodologies is currently engaging the attention of leading practitioners of system dynamics. There is a great deal of concern because of the isolation of system dynamics from other techniques and because of methodological issues in system dynamics that the field of soft OR has already begun to address. There is much benefit to be derived from a dialogue between the practitioners of system dynamics and those of soft OR (Lane, 1994).

At the time when system dynamics was being founded, there was a conscious separation of it from OR. Forrester (1968a) recognized the need for the practice of management to evolve from being an art but was nevertheless 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). 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.

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 complementarist 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 rely 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, synergestics, 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. In the same vein, 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.

The primary argument of the paper is to enrich the methodology of system dynamics by establishing an interface with structural equation modeling. This becomes critical while modelling social systems incorporating soft variables whose measurement is beset with the problems of systematic and random measurement errors. This would also prove helpful in ascertaining causal linkages among these soft variables. This is because there are certain 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. Causality or causal linkages are general to the paradigm of system dynamics. SD models are not appropriately judged using only standard statistical procedures. Firstly, SD models produce insight, not foresight. Secondly, an SD model constitutes an assembly of causal hypothesis about relationships between variables supporting time-evolutionary behaviour (Lane, 1995). Development of appropriate methodologies for establishing such causal linkages among soft variables used in a system dynamics model, thus, assumes critical dimensions.

2. Model Validation in System Dynamics

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 has ever been or even will be thoroughly validated….useful, illuminating, or inspiring confidence are more apt descriptors applying to models than valid'. According to Forrester (1968b), one cannot 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. 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 argues 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 argued 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.

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 incorporating 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. The 'real world' here is often fuzzy and messy. The soft variables cannot be measured directly and objectively. These are measured by quasi-quantitative methods and such 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. 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. Further, the causal linkages among the soft variables thus measured would have to be ascertained keeping in mind the systematic and random measurement errors inherent in such a measurement. Richardson (1996) while debating about the problems for the future of system dynamics, has made a comment that the field 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.

Validation as an issue of research and debate has largely eluded the practitioners of system dynamics. Barlas (1996) has pointed out that a survey indicates that little effort has been devoted by the system dynamics community to model validity and validation, 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 argues 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 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’ (page 211). What is, therefore, of importance to note here is 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 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 fax that it is considered to be complex. The approach which assumes that 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 need not be so. The variables in the model themselves could be perfectly measurable and quantifiable. There are examples of SSM precise where the variables in the problem situation were quite 'hard'. Moreover, in SSM we are not looking for developing a causal model which could then be further modelled in a system dynamics framework. There is a great difference between purely correlational and statistical models and SD models. SD models are intended to be useful devices for forecasting and control. However, SD models also 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. 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).

3. The Problems of 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 not to talk 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).

Problems have been encountered in developing system dynamics models incorporating soft variables. 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 are measured. A study of the system dynamics model of work climate of an R&D laboratory, developed by the authors and discussed above (Roy and Mohapatra, 1994), bears this out further. The causal relationships in this model, derived from correlation analysis, regression analysis, cluster analysis and multiple classification analysis, cannot be truly inferred or verified. Moreover, it is of importance to note here that the task of measuring the soft variables used in the model have been carried out using a quasi-quantitative framework, and, therefore, the reliability and validity of such measurements would have to be ascertained. Further, the relationships among the indices would also have to be ascertained in a way that would take into account this quasi-quantitative measurement approach. Only thereafter could a system dynamics model of such a soft system be developed. This would also help minimize judgmental scaling errors often encountered in such modelling initiatives. These questions assume criticality as the latent variables used in such a system dynamics model are derived from observed indicators. These indicators, in turn, are measured by quasi-quantitative methods. Therefore, the reliability and validity of the system dynamics model itself becomes subjective upon the reliability and validity of such measures.

4. Validity and Reliability of Quasi-Quantitative Measurement

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 degree 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. Campbell and Fiske (1959) have proposed two broad criteria for construct validation: convergent validity and discriminant 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).

Discriminant 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 interfaces. 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.

Understanding causal relationships among variables within a system and its consequent behaviour has for long been one of the key issues in system dynamics. Even in some cases, as suggested by Coyle (1998) and Wolstenholme (1999), a model can be entirely qualitative, consisting only of an influence diagram. The present paper argues for interfacing system dynamics and structural equation modeling. The central theme of structural equation modelling is establishing casual relationships among the latent 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).

5. The LISREL Approach to Structural Modelling

The path analytic model representing the structure of relationships as implied or ascertained can be tested with the help of LISREL technique (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). The model incorporates unobserved (latent variables), the relation between these and observed variables and an allowance for errors of measurement in the independent and dependent latent variables, and a causal model linking the latent variables together. It consists of two components - the measurement model and the structural model. 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 an 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).

LISREL 7.16 program (Joreskog and Sorbom, 1989) have 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 can also be used simultaneously (La Du and Tanaka, 1989).

5.1 A Brief Note on Lisrel Algorithm

A brief note on the LISREL algorithm could be given as follows:

The names of all the endogenous concepts are listed in a column vector η (eta) and names of all the exogenous concepts are listed in a column vector ξ (ksi). Let the number of endogenous concepts be m so that η would be an (m x 1) vector. Similarly, let the number of exogenous concepts be n (the total number of concepts thus being (m + n)) so that ξ would be a (n x 1) vector.

The first basic equation encapsulates all the postulated direct effects among the concepts and is given by:

$$\underset{(mx1)}{\eta} = \underset{(mxm)}{B}\,\underset{(mx1)}{\eta} + \underset{(mxn)}{\Gamma}\,\underset{(nx1)}{\xi} + \underset{(mx1)}{\zeta} \qquad \text{...(1)}$$

The sizes of all the matrices and vectors are determined by the substantive conceptual model.

Since B and Γ are matrices containing structural coefficients β and γ respectively (to be estimated), equation (1) states that each endogenous concept is a linear combination of all other conceptual variables in the model and an error variable ζ (zeta). All the diagonal elements in the matrix B are zeros such that no given η has a direct effect on itself. Similarly, if some of the endogenous variables are not directly influenced by any specific endogenous or exogenous variables, the same could be accommodated by inserting zero entries in B or Γ.

There are two equations that link the conceptual variables to the observed indicators. The first equation links the endogenous concepts to the endogenous indicators.

$$\underset{(p\text{x}1)}{y} = \underset{(p\text{x}m)\,(m\text{x}1)}{\Lambda_y \eta} + \underset{(p\text{x}1)}{\varepsilon} \qquad ...(2)$$

The second equation links the exogenous concepts to the exogenous indicators.

$$\underset{(q\text{x}1)}{x} = \underset{(q\text{x}n)\,(n\text{x}1)}{\Lambda_x \xi} + \underset{(q\text{x}1)}{\delta} \qquad ...(3)$$

The above equations state that any measurement reflects both the theoretical phenomenon it is intended to capture and any error in the measurement procedure. Here p denotes the number of endogenous indicators ($p > m$) and q denotes the number of exogenous indicators ($q > n$). Since it is possible to have several indicators of a single concept, the number of endogenous (or exogenous) indicators may be larger than the number of endogenous (or exogenous) concepts. The entries made in the (lambda) matrices Λ_y and Λ_x represent structural coefficients λ^y and λ^x respectively (to be estimated). They represent the degree of correspondence between the measurement and the concept, which when standardized ranges from 0 (no correspondence) to 1 (perfect correspondence). The symbols ε (epsilon) and δ (delta) are error variables specifying the cumulative effects of excluded variables and purely random measurement errors on the observed y and x variables. It would be assumed, as in regression, that all the three error variables have zero mean.

Four more matrices of coefficients are required to be estimated to complete the specification of the general model. These are all variance/covariance matrices. The first matrix Φ (phi) contains the covariances among exogenous concepts. Matrix Ψ (psi) contains the covariances among errors or structural disturbance terms influencing the endogenous concepts signifying the effects of some of the concepts excluded from the model on two of the endogenous concepts. Similarly, if some common cause contributes to two of the measurement error variables in the equation for the observed y (or x) variables, this would imply that the measurement error variables ε (or δ) would be correlated and hence would have some covariance to be recorded in Θ_ε called theta sub epsilon (or in Θ_δ called theta sub delta). All these four matrices share the properties of being square and symmetric matrices with positive diagonal elements (since these are variances). If the variables are standardized, these matrices become correlation matrices.

The model-implied covariance matrix among all the observed indicators without distinguishing whether they are indicators of the exogenous concepts (x) or of the endogenous concepts (y) as implied by the estimated model, that is, the numbers in the eight matrices described above, is denoted by Σ (sigma) having the order (p+q) x (p+q). This estimated covariance matrix is given by

$$\Sigma = \frac{\Lambda_y \,[\,(I-B)^{-1}\,(\Gamma\Phi\Gamma' + \Psi)\,(I-B)^{-1\prime}\,]\,\Lambda'_y + \Theta_\varepsilon \quad \Lambda_y\,(I-B)^{-1}\,\Gamma\Phi\Lambda'_x}{\Lambda_x\,\Phi\Gamma'\,(I-B)^{-1\prime}\,\Lambda_y{}' \qquad\qquad \Lambda_x\,\Phi\,\Lambda_x{}' + \Theta_\delta} \qquad ..(4)$$

The above equations are written with the assumption that the various error terms are independent of the concepts and of one another. However, LISREL provides the advantage that the parameters of the default model can be altered. Indeed, the assumption that there are no common response tendencies influencing the measures in a similar way and consequently, the indicators chosen to reflect the underlying concept are all unique, could be violated. This was shown in the previous chapter while dealing with the measurement model.

It must be stressed that Σ is a model implied variance/covariance matrix among the observed indicators x and y. For any set of values inserted in the eight matrices given above, one and only one covariance matrix among the observed indicators is implied by the equation. The actual observed covariance matrix among all the indicators is denoted by S. The closeness of the match between Σ and S gives not only a criterion for deciding which of the several alternative models is better but also a criterion for determining the best estimates for the free coefficients in any given model.

If a random sample of N individuals is selected from a multivariate normal population having a covariance matrix Σ, the likelihood of finding a sample with covariance matrix S is given by the Wishart distribution (Hayduk, 1987). The maximum likelihood (ML) estimates are computed by maximization of the log likelihood ratio (where the likelihood ratio is equal to the ratio of the likelihood for any given model to the likelihood with a perfectly fitting model) given by

$$\text{log likelihood ratio} = -1/2n[tr(S\Sigma^{-1}) + \log |\Sigma| - \log |S| - (p+q)] \quad ....(5)$$

where n = N - 1.

The above is equivalent to minimization of the function in brackets, called F given by

$$F = \log |\Sigma| + tr\,(S\Sigma^{-1}) - \log |S| - (p+q) \quad . \qquad ...(6)$$

with respect to the free parameters in the eight matrices mentioned above. The function is non-negative and equals zero only when there is a perfect, that is when the estimated Σ equals S.

In case of non-perfect fit, the χ^2 (chi-square) measure is given by

$$\chi^2 = nF \quad . \qquad ...(7)$$

The degree of freedom for the χ^2 test are calculated as the difference between the total number of unique entries in the covariance matrix (the observed variances/covariances) and the total number of coefficients estimated in the model. This is given by

$$df = 0.5\ ((p+q)\ (p+q+1)) - t \qquad ...(8)$$

where t is the total number of estimated coefficients and (p+q) is the total number of observed indicators. The above equation is the difference between the number of coefficients that would be estimated for a perfectly fitting model and the total number of coefficients estimated in the real model, also called the target model. From this perspective, the degree of freedom represents the degree of representational compactness of the target model. Larger the value of the df, the more parsimonious is the prediction (implication) of an acceptably fitting Σ (Hayduk, 1987).

LISREL also gives t values of the parameter estimates (ML estimates divided by the standard errors of the estimates). A t value greater than 1.96 is generally regarded as evidence of statistical significance of the parameter under large sample multivariate normal distribution. The root mean square residual (RMSR) is a measure of the average of residuals which means the difference between the entries in the matrices S and Σ. Therefore, the same can be interpreted against the average values of variances and covariances in the S matrix.

6. Developing Causal Loops from Structural Equation Models

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. The broad results of the study have been presented in an earlier paper by Roy, Nagpaul and Mohapatra (1997). The detailed results of the study including the detailed 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 are being brought out in a subsequent paper.

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 study mentioned above 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 Figure 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, this conclusion might be a bit far fetched as R&D effectiveness has not been adequately explained by the model (as given by the value of the squared multiple correlation for the structural equation) and one should adopt caution while explaining the loop.

In conclusion, it is 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 of soft systems 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 indicators or the observed variables have to be ascertained in a way that takes into account this quasi-quantitative measurement approach. Only thereafter could a System Dynamics model of such a soft system be developed. This would also help minimize judgemental scaling errors often encountered in such modelling endeavours. Structural Modelling using LISREL 7.16 progamme is an approach to tackle these issue and problems and it also serves as a pre-validation exercise for the System Dynamics model.

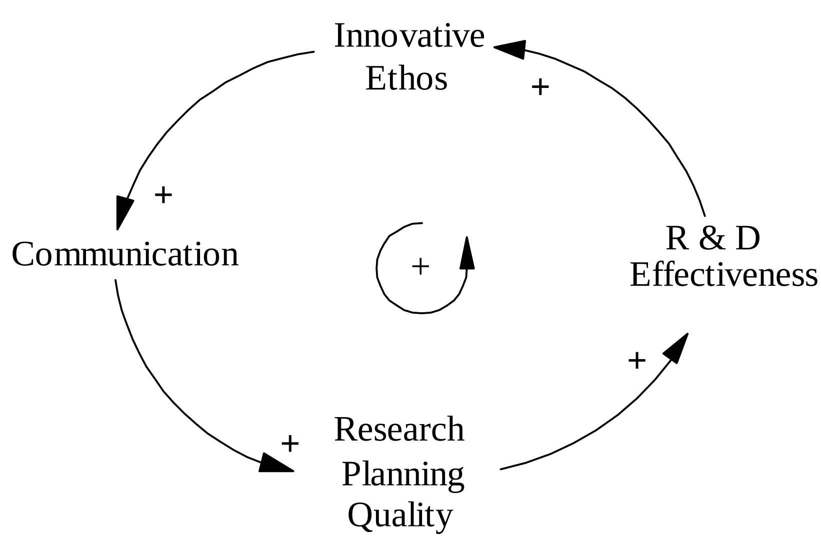

Fig:1. R & D Effectiveness Causal Loop

References

Ackoff, R.L., The Future of Operational Research is Past, *Journal of the Operational Research Society*, 30(2), 1979, pp. 93-102.

Andersen, D.F. and Rohrbaugh, J., Some Conceptual and Technical Problems in Integrating Models of Judgment with Simulation Models, *IEEE Transactions on Systems, Man and Cybernetics*, 22(1), 1992, pp. 21-34.

Bagozzi, R.P., Phillips, L.W., Representing and Testing Organizational Theories: A Holistic Construct, *Administrative Science Quarterly*, 27, 1980, pp. 459-489.

Barlas, Y. and Carpenter, S., Philosophical Roots of Model Validation: Two Paradigms, *System Dynamics Review*, 6(2), 1990, pp. 148-166.

Barlas, Y., Academics of System Dynamics: Its Core Definition, Topics and Terminology, *System Dynamics: An International Journal of Policy Modelling*, VII(1), 1995, pp. 1-16.

Barlas, Y., Formal Aspects of Model Validity and Validation in System Dynamics, *System Dynamics Review*, 12(3), Fall, 1996, pp. 183-210.

Barlas, Y., Model Validation in System Dynamics, *In System Dynamics: Exploring the Boundaries*, 1994 International System Dynamics Conference, University of Stirling, Scotland, UK, *Vol. System Dynamics: Methodological and Technical Issues*, System Dynamics Society, 1994, pp. 1-10.

Bohrnstedt, G.W., Measurement, in *Handbook of Survey Research*, Rossi, P., Wrightand, J, Anderson, A. (eds.), Academic Press, NY, 1983, pp. 69-121.

Bollen K.A., *Structural Equation with Latent Variables*, John Wiley and Sons, New York, 1989.

Bollen, K.A., Overall Fit in Covariance Structural Models: Two Types of Sample Size Effects, *Psychological Bulletin*, 107, 1990, pp. 256-259.

Browne, M.W., Generalized Least Squares Estimators in the Analysis of Covariance Structures, in, Aigner, D.J., Goldberger, A.S. (eds.), *Latent Variables in Socio-Economic Models*, North-Holland, Amsterdam, 1977, pp. 205-266.

Campbell, D.T., Fiske, D.W., Convergent and Discriminant Validation by the Multitrait-Multimethod Matrix, *Psychological Bulletin*, 56, 1959, pp. 85-105.

Checkland, P. and Scholes, J., *Soft Systems Methodology in Action*, Wiley, Chichester, 1990.

Checkland, P., Forbes, P. and Martin, S., Techniques in Soft Systems Practice, Part 3: Monitoring and Control in Conceptual Models and in Evaluation Studies, *Journal of Applied Systems Analysis*, 17, 1990, pp. 29-37.

Checkland, P., Model Validation in Soft Systems Practice, *Systems Research*, 12(1), 1995, pp. 47-54.

Checkland, P., OR and the Systems Movement: Mappings and Conflicts, *Journal of the Operational Research Society*, 34(8), 1983, pp. 661-675.

Checkland, P., Systems Thinking, Systems Practice, Wiley, Chichester, 1981.

Checkland, P., Techniques in Soft Systems Practice, Part 2: Building Conceptual Models, *Journal of Applied Systems Analysis*, 6, 1979, pp. 41-49.

Cole, S., Interests, Hopes and Fears - Can We Change the Future?, in Whiston, T. (ed.), *Uses and Abuses of Forecasting*, Macmillan Press, London, 1979, pp. 323-343.

Coyle, R.G. and Exelby, D., The Validation of Commercial System Dynamics Models, *System Dynamics Review*, 16(1), Spring, 2000, pp. 27-41.

Coyle, R.G., *Management System Dynamics*, Wiley, Chichester, 1977.

Coyle, R.G., *System Dynamics Modelling: A Practical Approach*, Chapman and Hall, London, 1996.

Coyle, R.G., The Practice of System Dynamics: Milestones, Lessons and Ideas from 30 Years Experience, *System Dynamics Review*, 14, 1998, pp. 343-366.
deGeus, A.P., Modelling to Predict or to Learn?, *European Journal of Operational Research*, 59(1), 1992, pp. 1-5.
Duncan, O.D., Introduction to Structural Equation Models, Academic Press, NY, 1975.
Forrester, J.W. and Senge, P.M., Tests for Building Confidence in System Dynamics Models, in *System Dynamics*, Legasto, A.A., Forrester, J.W. and Lyneis, J.M. (ed.), North-Holland, Amsterdam, 1980,
Forrester, J.W., Industrial Dynamics – A Response to Ansoff and Slevin, Management Science, 14(9), 1968b, pp. 601-618.
Forrester, J.W., Industrial Dynamics – After the First Decade, Management Science, 14(7), 1968a, pp. 398-415.
Forrester, J.W., *Industrial Dynamics*, Productivity Press, Cambridge, MA, 1961.
Forrester, J.W., System Dynamics, Systems Thinking, and Soft OR, *System Dynamics Review*, 10(2-3), 1994, pp. 245-256.
Forrester, J.W., *Urban Dynamics*, Productivity Press, Cambridge, MA, 1969.
Fox, J., *Linear Statistical Models and Related Methods with applications to Social Research*, John Wiley & Sons, New York, 1984.
Framinan-Tores, J.M. and Ruiz-Usano, R., Modeling Neural Networks using System Dynamics, in *Systems Approach to Learning and Education into the 21st Century*, Proceedings of 15th International System Dynamics Conference, August 19-22, 1997, Istanbul, Turkey, Barlas, Y., Diker, V.G.and Polat, S. (eds.), System Dynamics Society, 1997, pp. 167-170.
Greenberger, M., Crensen, M.A. and Crissy, B.L., Models in the Policy Process, Russel Sage Foundation, NY, USA, 1976.
Greene, K.B., Can System Dynamics be Theoretically Improved, and if so, Does it Matter Practically?, *Systems Research*, 11(3), 1994, pp. 3-21.
Hayduk, L.A., *Structural Equation Modeling with LISREL: Essentials and Advances*, The John Hopkins University Press, Maryland USA, 1987.
Howard, J.L., Frink, D.D., The Effects of Organizational Restructure on Employee Satisfaction, *Group and Organization Management*, 21(3), 1996, pp. 278-303.
Jackson, M.C., Beyond the Fads: Systems Thinking for Managers, Systems Research, 12(1), 1995, pp. 25-42.
Jackson, M.C., Critical Systems Thinking: Beyond the Fragments, *System Dynamics Review*, 10(2-3), Summer-Fall, 1994, pp. 213-229.
Jacobsen, C. Sociology and System Dynamics, *Dynamica*, 10(1), Summer, 1984.
Joreskog, K., Sorbom, D., *LISREL 7.16: Analysis of Linear Structured Relationship by Maximum Likelihood and Least Squares Method*, International Educational Services, Chicago, 1989.
Joreskog, K.G., A General Approach to Confirmatory Maximum-Likelihood Factor Analysis, *Psychometrica*, 34, 1969, pp. 183-202.
Joreskog, K.G., A General Method for Estimating a Linear Structural Equation System, in, Goldberger, A.S., Duncan, O.D. (eds.), *Structural Equation Models in the Social Sciences*, Seminar, New York, 1973, pp. 85-112.
Joreskog, K.G., Sorbom, D., *LISREL 8: Structural Equation Modeling with the SIMPLIS Command Language*, Scientific Software International, Chicago, 1993.
Joreskog, K.G., Sorbom, D., *LISREL VI User's Guide*, Scientific Software, Mooresville, IN, 1984.

Joreskog, K.G.,Structural Analysis of Covariance and Correlation Matrices, *Psychometrica*, 43(4), 1978, pp. 443-477.
Kennedy, M., Transforming Spreadsheets into System Dynamics Models: some Empirical Findings, in *Systems Approach to Learning and Education into the 21st Century*, Proceedings of 15th International System Dynamics Conference, August 19-22, 1997, Istanbul, Turkey, Barlas, Y., Diker, V.G.and Polat, S. (eds.), System Dynamics Society, 1997, pp. 175-178.
Kummer, S.D. and Schlange, L.E., Strengthening the Bridge between Qualitative and Quantitative Modelling: Contributions to the Toolbox for Analyzing Qualitative Models, in *Systems Approach to Learning and Education into the 21st Century*, Proceedings of 15th International System Dynamics Conference, August 19-22, 1997, Istanbul, Turkey, Barlas, Y., Diker, V.G.and Polat, S. (eds.), System Dynamics Society, 1997, pp. 543-549.
La Du, T.J., Tanaka, J.S., Influence of Sample Size, Estimation Method, and Model Specification as Goodness-of-Fit Assessments in Structural Equation Models, *Journal of Applied Psychology*, 74, 1989, pp. 625-635.
Landry, M., Malouin, J. and Oral, M., Model Validation in Operations Research, *European Journal of Operational Research*, 14, 1983, pp. 207-220.
Lane D.C., With a Little Help from our Friends: How System Dynamics and Soft OR Can Learn from Each Other, *System Dynamics Review*, 10(2-3), 1994, pp. 101-134.
Lane, D.C. and Oliva, R., The Greater Hole: Towards a Synthesis of SD and SSM, in *System Dynamics: Exploring the Boundaries*, Proceedings of 1994 International System Dynamics Conference, University of Stirling, Scotland, UK, Vol. Problem-Solving Methodologies, System Dynamics Society, 1994, pp. 134-146.
Lane, D.C., The Folding Star: A Comparative Reframing and Extension of Validity Concepts in System Dynamics, in Simada, T., Saeed, K. (eds.*), Proceedings of 1995 International System Dynamics Conference*, July. 30 – Aug. 4, Vol. 1, Lincoln, MA, System Dynamics Society, 1995, pp. 111-130.
Legasto, Jr., A.A. and Maciariello, J., System Dynamics: A Critical Review, in *System Dynamics*, Legasto, Jr., A.A., Forrester, J.W., and Lyneis, J.M. (eds.), , North-Holland Publishing Co., Amsterdam, 1980, pp. 125-142.
Long, J.S., *Covariance Structure Models: An Introduction to LISREL*, Sage, Beverly Hills, California, 1983.
Long, J.S., Estimation and Hypothesis Testing in Linear Models Containing Measurement Error: A Review of Joreskog's Model for the Analysis of Covariance Structures, in Marsden, P.V. (ed.), *Linear Models in Social Research*, Sage, Beverly Hills, California, 1981, pp. 209-256.
Mohapatra, P.K.J., Mandal, P. and Bora, M.C., *Introduction to System Dynamics Modelling*, Universities Press of India, Hyderabad, 1994.
Morecroft, J.D.W., Executive Knowledge, Models and Learning, *European Journal of Operational Research*, 59(1), 1992, pp. 70-74.
Mutec, J.E.S., Investigating the Dynamics of Employee Participation, in *System Dynamics: Exploring the Boundaries*, 1994 International System Dynamics Conference, University of Stirling, Scotland, UK, *Vol. System Dynamics: Methodological and Technical Issues*, System Dynamics Society, 1994, pp. 161-172.
Nordhus, W., World Dynamics: Measurements Without Data, *The Economic Journal*, 83, 1973, pp. 1156-1183.
Richardson, G.P. and Pugh, A.L., *Introduction to System Dynamics Modelling with DYNAMO*, MIT Press, Cambridge, MA.
Richardson, G.P., Problems for the Future of System Dynamics, *System Dynamics Review*, 12(2), Summer, 1996, pp.141-157.

Rios, J.P. and Schwaninger, M., Integrative Systems Modelling: Leveraging Complementarities of Qualitative and Quantitative Methodologies, *Proceedings of 1996 International System Dynamics Conference*, Cambridge, MA, System Dynamics Society, 1996, pp. 431-434.

Roy, Santanu and Mohapatra, P.K.J., Study of Work Climate in R&D Organizations: A System Dynamics Approach, in *System Dynamics: Exploring the Boundaries*, Proceedings of 1994 International System Dynamics Conference, University of Stirling, Scotland, UK, Vol. Production and Operations Management, System Dynamics Society, 1994, pp. 61-70.

Roy, Santanu, Nagpaul, P.S. and Mohapatra, P.K.J., Issues Facing Soft Systems Modelling: Structural Modelling in Relation to System Dynamics, in *Systems Approach to Learning and Education into the 21st Century*, Proceedings of 15th International System Dynamics Conference, August 19-22, 1997, Istanbul, Turkey, Barlas, Y., Diker, V.G.and Polat, S. (eds.), System Dynamics Society, 1997, pp. 171-174.

Saris, W.E. and Stronkhorst, L.H., *Causal Modelling in Non-Experimental Research: An Introduction to the LISREL Approach*, Sociometric Research Foundation, Amsterdam, The Netherlands, 1984.

Savicic, V. and Kennedy, M., The Transformation of Power Plant Investment Appraisal from a Spreadsheet into a System Dynamics Model, in *Systems Approach to Learning and Education into the 21st Century*, Proceedings of 15th International System Dynamics Conference, August 19-22, 1997, Istanbul, Turkey, Barlas, Y., Diker, V.G.and Polat, S. (eds.), System Dynamics Society, 1997, pp. 179-182.

Sorbom, D., Joreskog, K.G., The Use of LISREL in Sociological Model Building, *Ninth World Congress of Sociology*, Uppsala, Sweden, August 14-19, 1978.

van Gigch, J.P., *Applied General Systems Theory*, Harper and Row, New York, 1974.

Vazquez, M., Liz, M. and Aracil, J., Knowledge and Reality: Some Conceptual Issues in System Dynamics Modelling, *System Dynamics Review*, 12(1), Spring, 1996, pp. 21-37.

Wolstenholme. E.F., Qualitative versus Quantitative Modelling: The Evolving Balance, *Special Issue on System dynamics of the Journal of Operations Research Society*, 1999.

Wolstenholme. E.F., *Systems Enquiry: A System Dynamics Approach*, Wiley, Chichester, 1990.