

Incorporating Soft Variables Into System Dynamics Models: A Suggested Method and Basis for Ongoing Research

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Abstract

How to determine the impact of soft variables, including intangibles or social variables, and combining them as necessary with hard variables in system dynamics models is a significant challenge. This paper identifies a weakness in system dynamics modelling practice, that is, in reliably incorporating soft variables into system dynamics models. A method for incorporating such variables and a basis for further research is offered. The method combines systems thinking, research into causality analysis, multiple criteria decision analysis (conjoint analysis) and system dynamics modelling, in an integrated approach.

“To omit such [soft] variables is equivalent to saying that they have zero effect – probably the only value that is known to be wrong!” (Forrester, 1961: 57)

It is inescapable that from time-to-time we will need to build system dynamics models that take soft¹ variables into account. The challenge is to incorporate the influences of soft variables in ways that produce meaningful, reliable and repeatable results. We need to develop in-depth understanding of the roles and influences of soft variables. We must avoid making guesses about the influences that soft variables might have. Rather, we must create and repeatedly test dynamic hypotheses about soft variables. This will also demand that we comprehensively document our hypotheses about influences and how those influences are produced and combined, making the results available for peer review. Only when we do this will we build a sound appreciation of the nature and significance of soft variables both in our models and in the real world. Our track record in this area is not as good as it might be, as the following example suggests.

Pseudo-algebraic Expressions in System Dynamics Models – An Example

It is disturbing to encounter system dynamics models reflecting guesses about soft variables and as a result containing pseudo-algebraic expressions conveniently and artificially contrived to make a model or simulation behave as the modeller intends. Evidence of this practice can be found in models produced by students and experienced practitioners alike. Pseudo-algebraic expressions are a corruption of mathematical logic used to conveniently and artificially combine quantified soft variables. Such expressions may also involve mixes of hard and quantified soft variables.

The assumptions underlying this practice seem to be that soft variables, including that class of soft variables known as ‘intangibles’:

- conform to numerical scales;
- can be quantified in an absolute sense;
- quantification is both valid and universally acceptable; and
- once quantified, soft variables can be treated as dimensionless variables that can be added or multipliedⁱⁱ in exactly the same way as ordinary variables encountered routinely in system dynamics modelling are.

In their totality, these assumptions are erroneous; when taken individually, caution is needed. Further, any practice leading to the creation of pseudo-algebraic expressions, or their use, must be closely scrutinised.

In one particular example seen recently, a management flight simulator was built to assist in training managers to make decisions in the complex dynamic environment a particular firm operates. The underlying model contained around 60 variables, of which some 20 could only be described as being soft. Algebraic expressions made up of interesting mixes of hard and soft variables were built into the model to replicate the modes of behaviour that the modeller had identified as importantⁱⁱⁱ.

One expression in the model contained the soft variables *Organisational Performance*, *Qualifications Held By Individuals*, and *Individual's Motivation Level*. *Organisational Performance* was intended to describe how well the organisation performed (in an average sense, rather than in relation to discrete events) in making decisions, where decision makers were required to draw upon their own knowledge, skill and competence. *Qualifications Held By Individuals* described how well equipped individuals, in terms of formal qualifications held (including skills and competencies), were to make decisions and *Individual's Motivation Level* indicated motivation of individuals to take action, make the necessary decisions, or to implement a particular strategy. The resulting algebraic expression took the form:

$$\text{Organisational_Performance} = \sqrt{\text{Qualifications_Held_By_Individual} \times \text{Individual's_Motivation_Level}}$$

The abuse of mathematical logic and system dynamics principles in this example should be self-evident.

Despite obvious flaws in the model, the paper describing this model was peer reviewed and ultimately accepted for a recent international system dynamics conference. This suggests that as a group, we are prepared to accept these dubious modelling practices?

The intent of the modeller in producing this simulator was genuine although surprisingly naïve. The modeller apparently set out to do exactly what we teach, that is, to replicate

observed reference modes of behaviour. Our actions, both in terms of learning and system dynamics modelling practice are both misguided and naïve if we do not critically investigate why and how reference modes of behaviour are produced. In this instance, it seems that the modeller was actually mimicking what he saw as an important reference mode of behaviour without having a clear understanding of how that particular reference mode was actually created in the real world, or if he did he did not have the necessary tools (either physical or intellectual) to build a faithful representation of the causal mechanisms.

In this instance, and probably of greater concern is that how the particular reference mode of behaviour was actually created is unlikely ever to be questioned by anybody subsequently flying the management flight simulator in a training session. This is because the underlying structure of the model and its code, that making the simulator behave as it does, are masked from the players. Players, like the layperson in many real-life systemic problem situations will focus on the responses to their actions, rather than the (obscured) mechanisms producing the responses. The absence of essential critical analysis in such instances is very likely to lead to the unfortunate consequences that:

- poor practices become embedded in the design of simulations;
- erroneous conclusions are drawn about systemic causality, where soft variables are involved; and
- fallacious learning experiences occur.

This suggests we must look seriously at the treatment of soft variables in system dynamics modelling.

Need to Take a Hard Look at Soft Variables in System Dynamics Models

Sterman (2002: 522-523) makes the following points regarding soft variables in system dynamics models:

- Soft variables should be included in our models if they are important to the purpose.
- Omitting structures of variables known to be important because numerical data are unavailable is actually less scientific and less accurate than using your best judgement to estimate their values. Omitting concepts because they have no numerical data is a sure route to narrow model boundaries, biased results and policy resistance.
- We must evaluate the sensitivity of our results to uncertainty in assumptions – whether we estimated the parameters judgmentally^{iv} or by statistical means.
- It is important to use proper statistical methods to estimate parameters and assess the ability of the model to replicate historical data when numerical data are available. Rigorously defined constructs, attempting to measure them, and using the most appropriate methods to estimate their magnitudes are important antidotes to causal empiricism, muddled formulations and erroneous conclusions we often draw from our mental models^v.
- Most importantly, we should not accept the availability of data as given, as outside the boundaries of our project or research. We must ask why concepts our modelling suggests are important have not been measured. Frequently it is because no one thought these concepts were important...[stemming] from the narrow boundaries of our understanding.
- Human creativity is great: once we recognise the importance of a concept, we can almost always find ways to measure it. Today, many apparently soft variables such as customer

perceptions of quality, employee morale, investor optimism, and political values are routinely quantified with tools such as content analysis, surveys, and conjoint analysis ^{vi}.

- Of course all measurements are imperfect. Metrics for so-called soft variables continue to be refined, just as metrics for so-called hard variables are. Quantification often yields important insights into the structure and dynamics of a problem. Often, the greatest benefit of a modelling project is to help the client see the importance of and begin to measure and account for soft variables and concepts previously ignored.

Simply put, we need to take soft variables into account when they are likely to have an impact; priority for incorporating such variables, as in the case of hard variables, must be based on the likely extent of their impact. If these variables are likely to have an impact and are, therefore, worthy of inclusion in our models, we should measure them if we can. If we cannot measure them, we should estimate them as best we can by methods that give consistent, repeatable and reliable results.

We cannot afford to take shortcuts and indulge in poor modelling practices regardless of how tempting and convenient it might appear to be at the time; to do so could seriously damage confidence in the system dynamics modelling discipline or, even worse, destroy our credibility.

Purpose of This Paper

How to determine the impact of soft variables, including intangibles or social variables, and combining them through the system dynamics modelling process with hard variables is particularly vexing ^{vii}. This paper offers a method of incorporating soft variables into system dynamics models. The method combines systems thinking, research into causality analysis, multiple criteria decision analysis ^{viii} and system dynamics modelling, in an integrated approach.

Concerns About Soft Variables Raised Previously

Prior to Sterman (2002), Nuthmann (1994) and Coyle (1999, 2000) raised concerns about the meaning and impacts of soft variables in our system dynamics models, the way soft variables are handled, the handling of mixes of soft and hard variables in system dynamics models and validity of models ^{ix}.

Improving Ways of Measuring Soft Variables

Clearly, investigating and implementing better ways of measuring soft variables will help our quest. For example the system dynamics discipline could benefit greatly from having an intangible assets register. By this I mean a compendium of information about the nature of intangibles including a set of appropriate scales and measures by which we can gauge the 'soft' inputs to our models.

An intangible assets register might tell us how to measure or compare measurements made of, for example, motivation, competence, or stress levels and a whole range of other intangibles we know actually impact on performance of organisations and which we might wish to take into account in system dynamics models. Sveiby, Linard and Dvorsky (2002) have addressed the subject of an intangible assets register for system dynamics modelling where intangibles need to be included. The creation of a robust, practical, meaningful and verifiable way of measuring these intangibles would form an important foundation for development of system dynamics models.

The creation of an intangible assets register and commitment to the progressive validation of the methods of measurement, and eliminating the sources of variation in the values assigned

to intangibles in modelling, would be of enormous assistance. Work on an intangible assets register is still in its infancy and considerable research is required. Results would have to be validated, widely published and critically reviewed so that a valuable compendium of models involving soft and intangible variables is built and made accessible for widespread use. The system dynamics community should embrace this research, particularly because of the need to shore up a significant weakness in current modelling practice.

We need both an intangible assets register, and robust methods for combining these intangibles. Those methods exist^x and are described briefly in this paper.

Estimating Values of Soft Variables

A method for estimating variables, in instances where data is not available but experienced or expert personnel are, was enunciated by Ford and Sterman (1998). This method is equally applicable to the task of estimating soft variables in the absence of comprehensive data sets. The method involves polling and gaining consensus amongst those most experienced in a problem situation. Similar techniques have existed for many years, albeit in different guises^{xi}. They are seen as essential rather than optional tools we need in our system dynamics modelling toolbox.

Scales Applicable to Soft Variables

We must be very careful with assumptions about the scales, that is, nominal, ordinal and ratio scales that might, or might not, be applicable to soft variables. Many soft variables are not amenable to being 'scaled' in any absolute sense, in which case anything other than a comparative measure might be misleading or inappropriate, and ratio scales can lead to confusion when applied to different baselines.

In our opening example, the nominal scale used to measure *Qualifications_Held_By_Individuals* and ratio scale would be needed to measure *Individual's_Motivation_Level* bring attendant problems of incompatibility. They simply cannot be treated as the modeller did. We might imagine *Qualifications_Held_By_Individuals* to be measured in terms of numbers of relevant subjects taken as part of a degree or diploma held in a relevant discipline, applicable training courses completed or competencies the individual possesses measured according to a set of predefined criteria. Estimating and quantifying *Individual's_Motivation_Level* is somewhat more problematic.

Dimensionless and Normalised Soft Variables

Further, for algebraic expressions involving soft variables to make sense in terms of combining their influences, each of the variables would need to be dimensionless^{xii}. One useful way of treating soft variables, once we have ascertained that it is practical and valid to apply scales to them, is to treat them as having values in the range 0-1.0^{xiii}. This is applied by pair-wise consideration of the relationships between linked variables. Any influencing variable has an influence on the influenced variable also within normalised scales, that is, from zero up to its expected maximum, to which a value of 100% (1.0) is assigned.

Integrated Methodology Briefly Described

Once the causal structure involving the most important and relevant soft variables has been captured in the form of a causal loop diagram^{xiv} causal analysis and multiple criteria decision analysis are used to determine aggregated soft variable inputs to calculation of parametric values that, in turn, control flows through our system dynamics model.

Graphing Influences Between Pairs of Variables

For each pair of linked soft variables in our casual loop diagram we can develop causal relationship depictions such that, for example, the level $a(n)$ of an input variable ‘A’ produces an influence $\delta_{a,b}(n)$ on the output variable ‘B’^{xv}. See Figure 1. Here n is the iteration number, $\delta_{a,b}$ is the influence of ‘A’ on ‘B’ in the corresponding iteration and the lower case letters (e.g. $a(n)$) indicate the values taken on at each node in the iteration indicated.

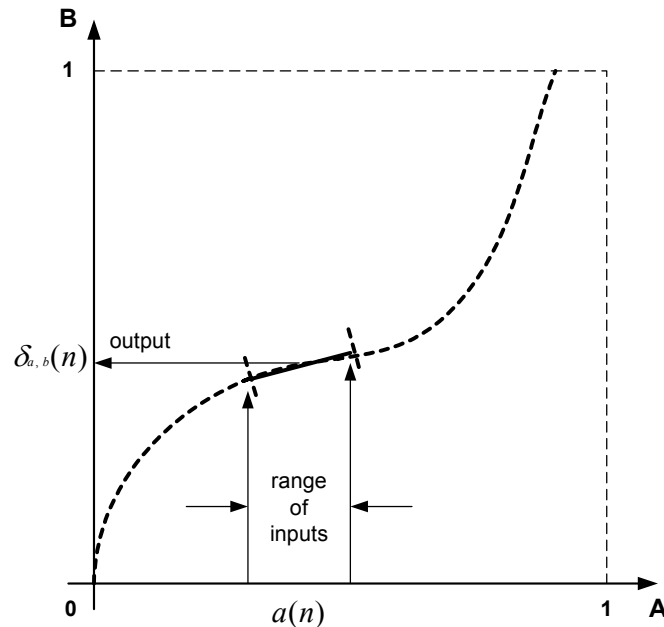


Figure 1. Causal Relationship Between Node A and Node B

Similar relationships can be developed, that is, derived from information in our (future) intangible assets register or estimated, as necessary, by employing a panel of expert or experienced personnel, using the technique explained by Ford and Sterman (1998). In this way, causal relationships can be developed for all relationships, A-B, B-C, C-N, and etc., shown in Figure 2. In the simplest case, the graph depicting the causal relationship will be a straight line. However, the general case is taken to be non-linear. Because of the computational effort that would be involved, no attempt is made to create a polynomial fit of these curves. Rather, the curve is approximated by a series of straight-line segments. See Figure 1. The mid point of each line segment is used to return the output for an input at any point on a given segment. This technique is used to greatly simplify the calculations^{xvi}.

Causal Loop Diagrams Depicting Linkage Between Soft Variables

To develop our first approximation of the algebra needed to control the auxiliaries or concentrators, and hence flows through our stock and flow model, we depict the influences that we need to combine using a causal loop diagram, as is accepted system dynamics modelling practice. However, at this stage we aim to treat soft variables separately from hard variables, producing a single, aggregated influence which will then be applied to selected hard variables in our stock and flow model. We draw a causal loop diagram^{xvii} to depict the total influence of a set of variables to be included in an auxiliary or concentrator^{xviii} we might produce this in a generic form as shown at Figure 2^{xix}. Here the darker arrows indicate the (incomplete) main loop identified to establish the correct sequence in the calculation of causal influences.

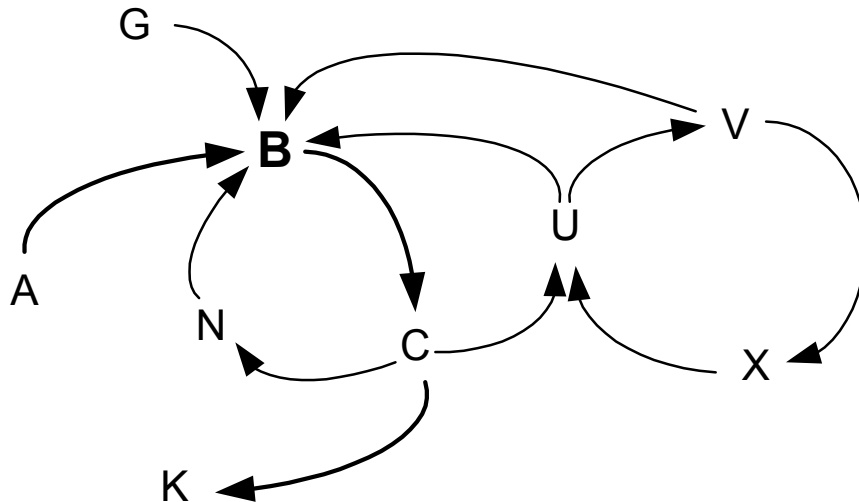


Figure 2. Generic Causal Structure

To each causal link we assign the information depicted in Figure 3, taking into account the nature of the causal relationship (influence) between linked pairs of variables as depicted earlier. See Figure 1. At this stage, we assign an ‘importance’ or ‘preference’ weighting (e.g. $w_{a,b}$) to each link in our causal loop diagram, having determined $\delta_{a,b}$ for the relevant iteration.

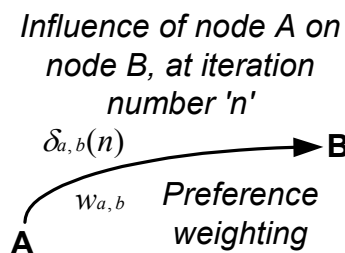


Figure 3. Information Required for Calculation of Influences Across Each Causal Link

Once the initial values ^{xx} have been estimated for each link, that is, in terms of both influence and weighting, it is necessary to calculate the post-initialisation value, $b(n+1)$ produced at node B. The specific sequence of calculation intended to avoid double counting of influences is shown in Figure 4, where the results of preceding iterations is shown at the bottom with the iteration currently under consideration being at the top.

$$\begin{array}{cccccc}
 b(n+1) = & \delta_{a,b}(n+1) & + \delta_{g,b}(n) & + \delta_{n,b}(n) & + \delta_{u,b}(n) & + \delta_{v,b}(n) \\
 & \nearrow & \nearrow & \nearrow & \nearrow & \nearrow \\
 & g(n-1) & n(n-1) & u(n-1) & & \\
 & & \uparrow & \uparrow & \uparrow & \\
 & & \delta_{c,n}(n-1) & \delta_{c,u}(n-1) & \delta_{x,u}(n-1) & \\
 & & \uparrow & \nearrow & \uparrow & \\
 & & c(n-1) & & v(n-1) & \\
 & & \uparrow & & \uparrow & \\
 & & & & & \uparrow
 \end{array}$$

$$\begin{array}{ccc} \delta_{b,c}(n-1) & & \delta_{u,v}(n-2) \\ & & \uparrow \\ & & u(n-2) \end{array}$$

Figure 4. Sequence of Calculation of Influences

This formulation assumes that the influences are added rather than being combined according to some other scheme. To ensure the totality of influences at any node never exceeds 1.0, it is necessary to set to unity the sum of weightings applied to links influencing each node. At 'B' this would be expressed as:

$$w_{a,b} + w_{g,b} + w_{n,b} + w_{u,b} + w_{v,b} = 1.0$$

These weightings are applied to the influences on each link having an impact at 'B' for that iteration. For example, when the weightings are applied:

$$b(n+1) = \delta_{a,b}(n+1).w_{a,b} + \delta_{g,b}(n).w_{g,b} + \delta_{n,b}(n).w_{n,b} + \delta_{u,b}(n).w_{u,b} + \delta_{v,b}(n).w_{v,b}$$

It is important to note here that when establishing the weightings there is a need to ensure consistency in application of the weightings simultaneously at nodes (where they sum to unity), in connected links and loops, and across the more remote links and loops^{xxi}.

Challenges Confronted During Development of this Methodology

The challenges confronted in developing this methodology^{xxii} included:

- Finding ways of taking into account the causal influences for every link depicted in the causal loop diagram.
- Determining the influences across each causal link:
 - Taking the correct sequence of calculations into account.
 - Avoiding double counting.
- After allocating weightings to the arrows influencing a node, assigning values to each weighting to ensure:
 - Total of preference weightings applied to each of the influences we require to combine at each node sums to 1.0. This is a convenient device for which no detailed justification is offered, other than to avoid computational irregularities.
 - That preference weightings reflect due consideration of the importance of each causal link, for example, weighting applied to a particular link is not overly weighted or given too little weight.
 - Consistency in the pair-wise comparisons involving weightings applied to all links.

Practical difficulties encountered include:

- Variations in estimating soft variables.
- Sensitivity, of the process of calculating the total influence at a node, to changes that are made to the shape of influence relationships or to the weightings applied to individual connecting links.

- Initialising the causal loop diagram, that is, choosing sets of nodal values, causal influences across links and importance weightings that do not produce computational inconsistencies^{xxiii}.
- Selecting the number of straight-line segments to approximate curves in each of the pair-wise causal relationship such as shown in Figure 1. Short segments are used where we have confidence in the shape of the curve, longer segments are used where confidence is low:
 - When a large number of short line segments are used, calculations become computationally demanding.
 - When a small number of longer line segments are used, attempts to initialise a causal loop diagram result in ‘hunting’ back and forth between values returned from subsequent causal graphs encountered in the sequence of calculations.

A number of important issues require further research:

- Are influences at a node additive^{xxiv} as we have assumed? Research into heuristics in decision making suggest that if influences are additive and we consider all influences according to their importance, we apply Franklin’s Rule^{xxv}. However, Gigerenzer, et al., 1999 and Klein 1998 suggest that we actually base choice and decision making on a variety of heuristics. It follows that Franklin’s Rule may only be one of several schemes we might consider when designing algorithms for combining influences at a node^{xxvi}.
- Can we actually assign meaningful values at each of the nodes – exactly what do these nodal values mean?

The Way Ahead

The most obvious question here is... ‘why go to the amount of effort the application of this methodology suggests?’ If sufficient justification cannot be found in the example cited at the beginning of this paper, it surely must be found in the concerns raised over nearly a decade by Nuthmann (1994), Coyle (1999; 2000) and most recently by Sterman (2002).

Further, system dynamics texts and teaching almost universally ignore the problems of handling soft variables seemingly because it is simply too difficult. That avoidance must ultimately translate to lack of skill and lack of consistency in the practice of our art; and whilst this remains the case, system dynamics modelling will remain an art rather than being recognised as science.

Concurrent and ongoing work by Sveiby, Linard and Dvorsky (2002) also needs to be pursued and incorporated into system dynamics modelling practice to assure consistency in the determination of values assigned to intangibles in system dynamics models.

A concerted research effort is needed to gauge the efficacy of the method offered here, or to find alternatives. The products of research work of McLucas (2001; 2002) and practical work by Schmidt and Gary (2002) suggests that such methods have both promise and applicability. However, except in simple cases, considerable computation is needed, including the employment of search techniques which are impractical to manually apply. So, these methods need to be automated^{xxvii} and the software tool must be designed to interface with existing system dynamics modelling software applications.

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ⁱ 'Soft' means qualitative in nature. It does not mean unmeasured, estimated, uncertain or fuzzy. Soft variables can be difficult to measure or estimate, and it may be difficult or impractical to apply universally-applicable scales to them. Soft variables include a class of variables referred to as 'intangibles'. For example, we might argue that 'quality of leadership' if used as a variable in a system dynamics model could be measured according to the presence or absence of certain leadership qualities; on this basis we could establish a measure of quality of leadership. However, the individual leadership qualities such as personal integrity would be considered as intangibles. We might be able

to assess that an individual has personal integrity, but applying a score to an individual leader on the basis of some universal 'integrity' scale may prove problematic at best. This is the nature of intangibles.

ⁱⁱ Using conventional algebraic operators.

ⁱⁱⁱ A strong criticism made by many system dynamics modellers of econometric modelling is that in econometric modelling there is an implicit assumption that statistical correlation among a group of variables is seen as causality. In effect this is what modellers are doing when they produce the type of pseudo-algebraic expressions described in our opening example. With statistical correlation it is easy to ignore demands for dimensional consistency. For example, in examination of the algebraic expression ' $y = ax^2 + bx + c$ ', found during statistical / correlation analysis, if 'y' and 'x' have the same dimensions 'q', then 'a' must, by definition, have the dimensions '1/q', and 'b' must be dimensionless and 'c' must have dimension 'q'.

^{iv} See Ford and Sterman (1998).

^v See Homer (1996; 1997).

^{vi} This paper takes the techniques described by Schmidt and Gary (2002) a step further by describing a method for the general handling of soft variables as well as those which involve preferences, that is, combining multiple criteria decision analysis (conjoint analysis) and systems thinking.

^{vii} Integrating hard and soft systems analysis, including the handling of soft variables were subjects of the author's PhD dissertation.

^{viii} For a comprehensive explanation of multiple criteria decision analysis, see Belton and Stewart (2002).

^{ix} The problem of how to treat mixes of hard and soft variables is not unique to system dynamics modelling, it also arises in systems engineering where there is also ample evidence of the existence of practices whereby soft variables are quantified using questionable methods.

^x The technique has been demonstrated by McLucas (2001: 314-349).

^{xi} These techniques are a variation of the Delphi Technique (Brown, et al. 1969).

^{xii} Designers of new system dynamics software applications such as Powersim® Studio have gone to considerable effort, and for very good reason, to make it difficult for modellers to build models that ignore the units associated with either soft or hard variables. It has been conventional SD practice to incorporate soft variables by use of the following causal logic: *Level of Workforce Motivation* (a soft variable) leads to (or causes) a *Measurable Effect of Motivation on Output* (a hard variable), which, in turn, contributes to *Output* (a hard variable). It has been a deliberate choice of Powersim® Studio designers to inhibit calculations involving a mix of dimensionless and dimensioned variables, in effect forcing the model builder to defining of units for all variables used in every model. The methodology described in this paper might demand the creation of a 'dimensionless modifier' to be used in such software applications. The 'dimensionless modifier' would input, to the model, the aggregated effect on a hard variable created by soft or intangible variables.

^{xiii} An example of normalisation might be explained with reference to an illicit drugs usage example. The total number of drug users might be estimated on the basis of a proportion of the total of the population. An estimate of expected growth, say 10%, over the period during which this study is to be conducted would lead to the total numbers we might expect. In a city of 300,000, it might be estimated that there is a maximum of 330 cocaine users (one in 1,000 plus 10%). It would then be estimated that a maximum of 330 users would each consume x grams of cocaine per year on average; the quantity being determined from Police and medical historical records. Note that we are not interested in absolute numbers, *per se*, but the estimates are needed to enable normalisation of scales on the axes of each graph. Maximum values on each axis are normalised to unity. Rationale behind estimations made and normalisation calculations must be recorded for future reference, for consistency and peer review.

^{xiv} This method works equally for small numbers of soft variables not linked in a causal feedback structure.

^{xv} Here we must be careful not to confuse correlation and causality. Each graph must depict our own currently-existing dynamic hypotheses about causality. The starting point for the development of these hypotheses may be found in the process of investigating the correlation between variables. Whilst this may be necessary, it is unlikely to be sufficient. Causal relationships between linked pairs of variables will have to be subjected to continued critical examination.

^{xvi} The exact details are not provided in this paper; however, a full explanation of the fuzzy algebra calculation technique is contained in McLucas (2001: 314-349).

^{xvii} Output from multiple criteria decision analysis of causal loop diagrams is intended to be a single, weighted and non-dimensional factor which is then used to modify the algebra of an auxiliary or concentrator in which hard (rate controlling) variables appear.

^{xviii} We need a convention that identifies the output from this analysis with a label 'Soft / Intangible Variable (Dimensionless Modifier)'

^{xix} Schmidt and Gary (2002) in their conjoint (multiple criteria preference / decision) analysis treated causal influences as a hierarchy with each lower level being combined to produce the influence at the top of the hierarchy. The validity of their approach is not questioned but the extent of its applicability is. In this paper the aim is to demonstrate a generic approach applicable to systemic influences, that is, where multiple feedbacks might exist and influences need to be considered iteratively because they may change over time. Changes over time might stem from adjustments consumers, decision or policy makers (actors in our problem formulation) make in their thinking. These may result from advertising, market forces or shifts in perception by the actors involved.

^{xx} McLucas (2001) found that the process of initialising such a causal loop diagram (in the general case the main loop shown in bold is complete), can be difficult to calculate without resorting to the non-ideal fixing of values of selected nodes or by repeatedly adjusting the shapes of the curves that define the causal relationships.

^{xxi} It is easy to invalidate the rule that the sum of weightings at a node is unity because this rule applies simultaneously to all nodes whilst the pair-wise comparison of all weightings also is to be concurrently satisfied. To resolve this can demand quite sophisticated mathematical search techniques such as genetic algorithms.

^{xxii} Multiple criteria decision analysis techniques are used to support the combining of causal influences appearing in our causal loop diagram.

^{xxiii} This suggests the need to support the process by use of computationally-intensive, but powerful, mathematical techniques such as genetic algorithms.

^{xxiv} It is conceivable that influences might be multiplicative or combined in other ways. At this stage it is assumed that influences are added. The veracity of that assumption requires examination.

^{xxv} Franklin's Rule, named after US President Benjamin Franklin, is a technique which involves identifying all relevant factors then applying weightings to each on the basis of their considered importance. The idea is that the decision to be made must take into consideration all the prevailing factors according to their importance or their perceived influence on the problem.

^{xxvi} In contrast, we might only consider a single, important factor as we do when applying the 'Take-the-best' heuristic. See Gigerenzer, et al., 1999.

^{xxvii} Such as is being done through the development of the SD 'Front End Tool' described by McLucas (2001; 2002).