TOWARDS AN INTEGRATED, INTELLIGENT KNOWLEDGE BASED SYSTEM FOR DYNAMIC MODELLING

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ABSTRACT

Innovations in automated intelligent knowledge based systems (IKBS) including expert systems (ES) could have a major impact on the development of system dynamics methodology. This paper reports on the characteristics of an integrated system for modelling and managing complex, dynamic systems currently being developed. Essentially, the system consists of five sectors namely a simulation model; a set of quantitative measures as macros; means; a real world data set; an adaptive knowledge based system including an expert system; a policy decision making system. It is suggested that such an integrated approach to system dynamics could further enhance the usefulness of the methodology to modelling and managing complex systems.

INTRODUCTION

Intelligent, knowledge based systems (IKBS) are part of the more general area of computing science concerned with artificial intelligence (AI). Studies into I.K.B.S. are concerned with, "designing computer systems that for certain limited areas, emulate some of the characteristics of human thought - the ability to learn, reason solve problems and understand ordinary human language." (Shannon, et al, 1980, 276). Within this general area of intelligent, knowledge based systems, there has been a growing fascination with the development of expert systems (ES). One technical approach to developing expert systems is to try and write computer programs which will duplicate the results of learned skills or human expertise without concern for whether the processes going on in a computer are exactly the processes used by the real human expert. As Shannon puts it, "Expert systems (ES) applications should be differentiated from pure AI research because the primary goal of such applications is not to understand the basic mechanisms used by the human expert to arrive at a given result, but rather, it is to <u>consistently duplicate the results of a human expert</u>" (Shannon et al, 1980, 776 emphasis added). It is against this background of research into intelligent knowledge based systems, including expert systems, that the rest of this paper will attempt to integrate these concepts into conventional system dynamic modelling.

In the following section a conventional way of building system dynamic models is described. Whilst, no doubt, there are many ways in which each process could be described the purpose of this simple recipe for system dynamic modelling is to illustrate the way in which system dynamic models could be extended by integrating some concept of AI into our practice. In section three this traditional approach to system dynamic modelling is extended by introducing an intelligent knowledge based system (including an expert system) into the modelling process. It will be argued that expert systems which work in <u>virtual time</u> could be very useful to model builders and decision makers who are working with simulated and real time respectively. The way in which an expert system can be integrated into system dynamic modelling is illustrated by a hypothetical example from on-going research into carrying capacity. Finally, some of the unresolved technical and ethical problems are discussed.

SYSTEM DYNAMIC MODELLING PROCEDURE

There are various procedures for building models in science (Jeffers, 1978, Jørgensen 1986, Roberts et al, 1983). In figure 1 a tentative modelling procedure is outlined for system dynamic modelling. As can be observed the primary focus of all research at all times is to define the problem clearly. This is not a trivial task as a problem that is ill-defined is a problem which is unlikely to be solved. A problem can be defined as an unsatisfied need to change an unusual observation to an expected observation. A problem is solved when the unusual observation and expected observations are perceived to be the same. Often, this procedure is not correct at the first attempt and it needs an constant interplay between theoretical speculations and practical observations.

Once the problem has been clearly defined it is necessary to attempt some form of conceptualisation of the problem viewed as a system. The second phase of system dynamics modelling is an art which depends on the creative imagination of the researcher as well as his/her knowledge of the way in which the system functions. The latter can be gleaned, in part, from detailed study in the field or laboratory, by questionnaires, statistical analyses of data or through a thorough examination of previous studies. In system dynamic modelling this phase of conceptualisation is achieved, in part, by constructing a causal diagram or digraph of the system.

Model representation is the third phase of system dynamic model building. This stage consists essentially of translating the causal diagram or digraph into a computer flow chart. A flow chart is a partial representation of the sequence of operations which are necessary to solve a problem. Various conventional symbols are used in flowcharting. In system dynamics the conventional symbols for levels, rates and auxiliary equations using DYNAMO or DYSMAP can be inter-connected to form a multi-feed back loop stylized flow chart. These stylized flow charts are a diagrammatic representation of a set of completely recursive difference equations. In the fourth phase of model building the behaviour of the simulation model is compared qualitatively and quantitatively with the behaviour of the system of interest's reference mode. The reference mode represents either an empirical trajectory of one or more state variables such as the changing level of CO_2 (Carbon dioxide) in the atmosphere or a hypothesised mode of behaviour which model builders and decision makers would like a real system to achieve such as the reduction of CO (Carbon monoxide) in the urban environment.

Model evaluation is the fifth phase of model building and it is crucially important that parameter sensitivity tests and careful calibration are undertaken as well as rigorous forms of verification procedures are used including statistical analyses. The latter can be custom built by use of macros. Whilst the degree of correspondence between simulated and actual data is usually measured by conventional statistical techniques it is not the only form of model evaluation (Legasto et al, 1980). It is, however, important to note that system dynamic modelling, as in other forms of systems modelling, is an iterative process. It is often essential to refine the operational model by carefully repeating the first five phases of model building. Often this refinement of the original model is enhanced when quantitiative analyses are used.

The penultimate phase of system dynamic model building is concerned with the assessment of various policy alternatives. In the original use of the systems dynamics approach much emphasis was placed on the control and management of industrial and urban systems (Forrester, 1961, 1969). This emphasis on policy orientated research is still much in evidence as Forrester notes, "the ultimate test of a system dynamics model lies in identifying policies that lead to improved performance of the real system" (Forrester, 1980, 224). Despite the difficulties and ethical as well as political implications involved in actually carrying out such tests it is clear that many system dynamic model builders have overstressed the various policy alternatives embedded in system dynamic models at the expense of more rigorous research into their own models. It should, however, be obvious that if dynamic models are to be used as tools for implementing environmental management or socio-economic planning then it is essential that the model on which some of the policies may be based are sound. If there are major weaknesses in the models then clearly any policy recommendations based upon them must carry little or no conviction. (Wilson, 1970).

The final phase in system dynamic modelling is to use a well validated and stringently tested model in order to contribute to an understanding of a particular problem. In a hard system this understanding may lead to an efficient and effective solution to the problem. In soft systems, however, this understanding may lead to political ways to promote system change and evolution. If policies emanating from dynamic models are put into practice then it is essential that the real world system is carefully monitored to enquire into the ways in which the policy is effective. This does, of course, raise important questions concerning the ideology of control on the use of system dynamic modelling or other techniques (Gregory, 1980).

Phase 1	Problem definition
Phase 2	System conceptualisation
Phase 3	Model representation
Phase 4	Model behaviour
Phase 5	Model evaluation
Phase 6	Policy alternatives
Phase 7	Model use

Figure 1. System dynamics modelling procedure.

INTELLIGENT KNOWLEDGE BASED SYSTEMS

The modelling procedure outlined above has been used in many disciplines for several decades. Recently, however, intelligent knowledge based systems, including expert systems, have emerged as an important area of research activity in computing science. The term 'knowledge base', in this context, refers not only to the facts, but also to the relationships and rules governing the inter-relationships between the fact and conceptual models which have been developed in the past decade. The word 'intelligent' refers to the ability of the computer to make inferences from the conceptual model and factual data; to store these inferences along with the relevant data in its memory; and to use this new knowledge to help in the process of solving a specific, well defined problem. These developments in intelligent knowledge based systems have a potentially important role to play in the future development of system dynamics modelling. One way in which IKBS, including ES, can be integrated into system dynamics is illustrated in figure 2. As in the earlier approach to model building the problem is defined clearly; a conceptual model is created; a flow chart and program are then written to create a simulation model; the model behaviour is examined; sets of MACROS are built to calibrate and then test the models output with the real data as part of the process of model evaluation. At this point in the 'normal' modelling process an intelligent knowledge based system is introduced in order to facilitate the verification of the model and to aid decision making of alternative forecasts. As the introduction of an intelligent knowledge based system into the normal processes of systems dynamic modelling is relatively new it is worthwhile explaining the way a typical knowledge based expert system can function in system dynamic modelling. A typical intelligent knowledge based system consists of a knowledge base, an inference engine and a workspace. (Hawkins, 1985). The knowledge base consists of facts supplied by the user but can also include 'facts' introduced into the knowledge base by a simulation model acting as input. In this latter sense the inputs from the model represent a future state of the system which, as yet, has to be realized. The inference engine attempts to solve a problem by searching the domain of the knowledge in the knowledge base. In the case of an expert system the inference engine attempts to consistently duplicate the result that a human expert would make with the same information. In an <u>intelligent</u> knowledge based system this solution is stored together with the relevant data to aid the decision making process in the future. The workspace is an area of memory that is set aside in the computer for the storage of the description of the problem constructed by the simulation model or directly from facts supplied by the user. (Figure 2).

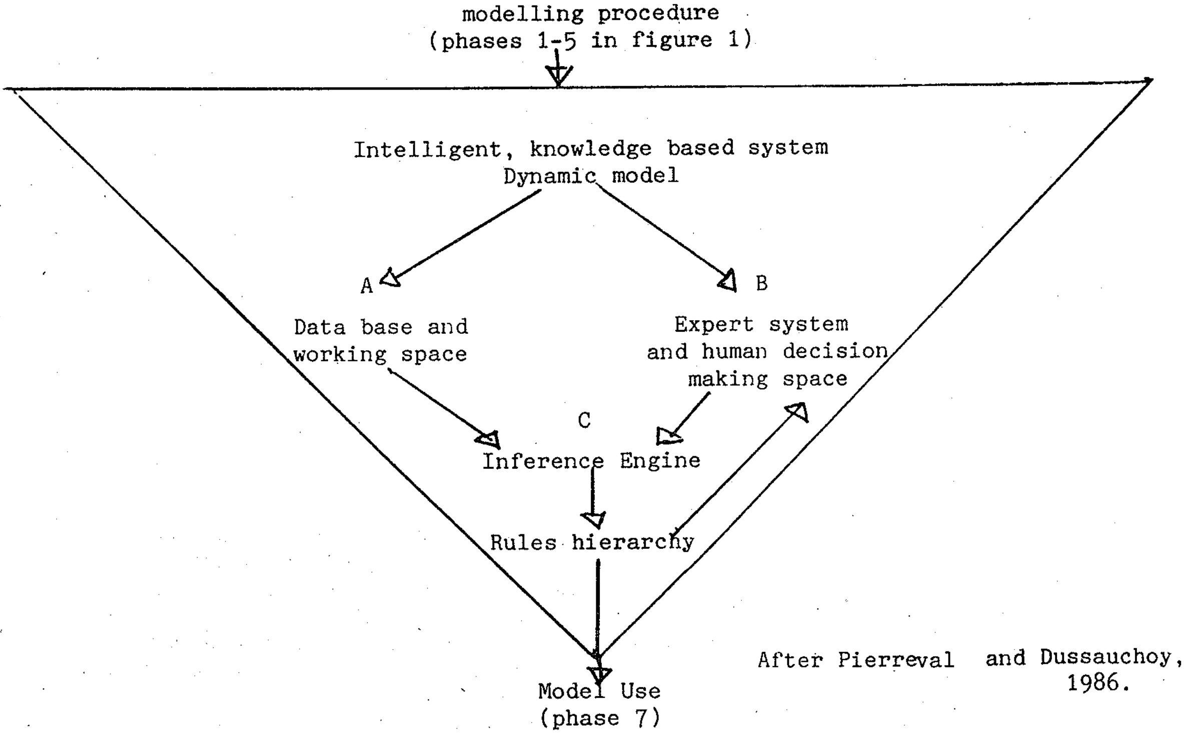

Figure 2. Intelligent knowledge based system integrated into system dynamic modelling.

In order that the intelligent knowledge based system is to be of use to the model builder or decision makers, it is important to make a threefold distinction in the temporal frames of reference which are used simultaneously by people. At the first level normal real time is used by us in our everyday activities - all our decisions are made in real time but they can have important implications for future events in real time as well as the other two time domains. The second time domain is that of simulated time i.e. the length of real time simulated in a computer model. For example in one minute of real time it is possible to simulate, say, two hundred years of 'real' time in a dynamic model. The third temporal frame is virtual time. This latter domain acts quickly so that the results and consequences of making one decision in the simulated time can then be examined over the length of the simulated time horizon operating in virtual time. This facility allows model builders to observe what would happen to the behaviour of the model if this decision option was activated in real time and allowed to run uninterrupted into a real future time.

The orthodox procedures used in system dynamics to evaluate forecasts are generally to activate one or more policy option in the simulated time domain and then observe how the system behaves. This simulated time is very small (usually seconds for socio-economic systems) when compared to the real time of the actual systems response to policy changes. This is shown in figure 3. Again, the actual choice of trajectory is made by the decision makers whilst the model, if valid, shows a series of possible futures.

The use of intelligent knowledge based systems, including expert systems, differs in that the future forecasts are not necessarily printed as possible future trajectories of the system in simulated time but as possible futures in virtual time. These possible futures in virtual time are processed rapidly during the DT-interval of the solution to the simulated models equations but run to the end of the length of the simulated period in the virtual time domain. The information received by the simulated model from these trajectories in the virtual time domain are then stored in the workspace of the knowledge data base system. These possible futures are then examined by the inference engine or expert system so that the 'best' alternative including the status quo could be selected. In a fully automated system the 'best' option would be selected - this would, however, assume that the expert system is as good if not better, than the frailties of human decision makers.

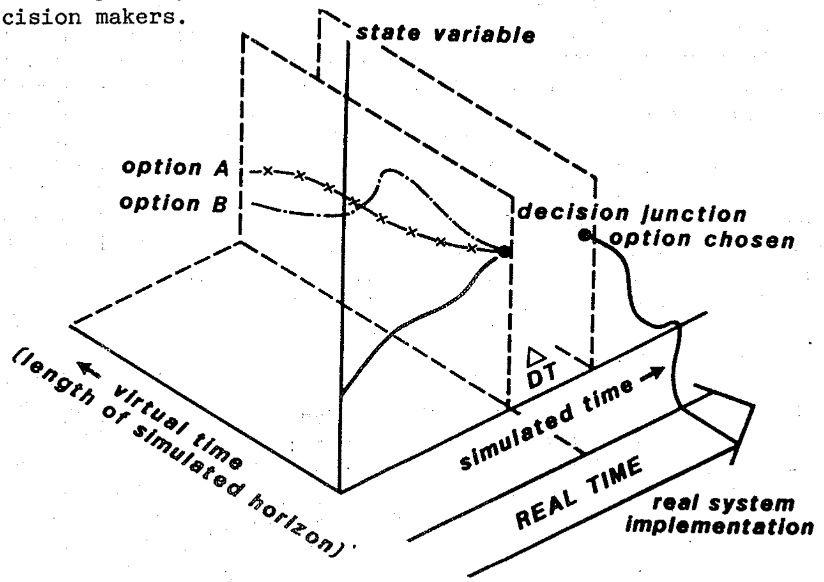

Figure 3. Virtual, simulated and real time in an expert system.

In order to illustrate the way in which this intelligent, knowledge based system can be integrated into normal system dynamic modelling an example from a study of carrying capacity in Kenya will be used. (Slesser et al, 1984). In a recent study Slesser and his co-workers attempted to identify "the consequences on national development of various actions or possible scenarios before they are implemented in order to see whether they are going to create a more sustainable or more developed society, given the existing population's resources, given the socio-cultural pattern and given its present state of development" (Slesser et al 1984, p.18). By building a simple system dynamics model named ECCO (Enhanced Carrying Company Options) a whole series of possible projections of development were produced. These scenarios ranged from unsustainable forecasts to several options which, in theory, are sustainable. By embedding the expert system with the structure of this model it is possible for the IKBS to select the 'best' option at the current real and simulated time. Furthermore, it is also possible for the expert system to examine possible scenarios in virtual time to see what would happen if the apparent 'best' scenario was, effected by a stochastic disturbance. Further work into this interface is under-way.

What advantage, if any, does this new approach to system dynamic modelling have over the orthodox procedures? The major advantage is that the use of an expert system in system dynamic modelling integrated in an adaptive knowledge based system permits the computer to select the 'best' option from its examination of the variety of options simulated in virtual time. Normally, policy makers only select the most suitable action from an examination of the trajectories of several forecasts printed out as simulated futures. Whilst there is little wrong with this procedure the major difficulty arises when one option is chosen from the simulation model and implemented in a real time system. Once the decision maker has chosen this course of action it is often difficult to reverse that decision and choose another more appropriate form of action. By simulating the options in virtual time and using the knowledge gained from these scenarios (stored in the data base) together with some objective choice directed by the expert system it is possible to quickly ascertain the 'best' possible policy to guide the real world system.

There are, however, three important problems which still have yet to be resolved. The first technical problem requires that the simulation in virtual time is completed very quickly - within the solution time (DT) of the model's simulated time - before proceeding with the dynamic simulation. This requires the use of efficient parallel processors which can explore a whole variety of options simultaneously before permitting the main DYNAMO program to proceed. The development in both hardware and software should eradicate or, at least, reduce this problem. A second technical problem is to overestimate the reliability of the 'expert system'. Despite the rapid advances in this area of research into artificial intelligence the expert systems are still crude. As Hawkins notes the user must recognise "the limits of the domain of expertise of the system. Expert systems can be useful; they can also be hazardous. The most obvious danger would be for a user to rely on a program that was not totally expert; one that had significant deficiencies in its knowledge base ... " (Hawkins, 1985 p.16). Third, even when these technical problems are overcome it is important that the models are robust and carefully tested before policies emanating from these models are put into practice. As Hare comments: "it is the public's privilege to choose politically among the options, but the scientist has to specify the range of possibilities and the means whereby the goals may be reached." (Hare, 1983, p.136). Clearly, the development of an integrated, intelligent knowledge based system for dynamic modelling is still in its infancy.

CONCLUSION

This paper has reported on the way in which expert systems can be embedded into the normal system dynamics modelling paradigm. Unlike the normal system dynamics paradigm, however, some forms of the decision making options for alternative policy evaluation are undertaken by the expert system rather than by the human decision maker. The way in which this technical problem is resolved is by allowing the DYNAMO compiler to work in virtual time to discover the possible impacts of these decisionsif the latter were implemented in the real world. By using a form of time warping in system dynamics a kind of relativity dynamics is developed (Keloharju, 1983; Zhixin et al, 1986). An illustration of this approach was given in the case of modelling carrying capacity options for a country.

The major advantage of this system is that during each simulation the expert system can remember the impact of previous simulated runs in virtual time and then decide which is the 'best' option for the simulation to proceed and calculate actions to ensue.. The major disadvantages in this approach is that it is technically difficult to allow time warping using DYNAMO. Furthermore, neither the expert system nor human decision makers are perfect - the best policy run may not meet the approval of other actors in the real system (Gardiner and Ford, 1980). Nevertheless, this integrated approach to system dynamics once developed has the potential for enhancing the methodology for modelling and managing complex systems.

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