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A note on the integration of system dynamics and economic models

Peter C. Smith[a,*], Ann van Ackere[b]

[a]*Department of Economics & Related Studies, University of York, York YO10 5DD, UK*
[b]*HEC Lausanne, Switzerland*

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Abstract

Equilibrium is probably the principal focus of most areas of economic analysis. However, the policy maker is often interested not only in the equilibrium predictions arising from an economic model, but also in the path taken by policy variables as they move towards that equilibrium. It is therefore likely that integration into a dynamic framework will frequently enhance the usefulness of an economic model. Recent developments in computer software mean that system dynamics offers a readily accessible methodology for making this principle operational. The approach is illustrated using an example from the British National Health Service, in which a traditional economic model of supply and demand is deployed within a system dynamics model. © 2002 Elsevier Science B.V. All rights reserved.

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1. Introduction

System dynamics (SD) dates back to the late 1950s, and interest in the methodology grew rapidly during the 1960s and early 1970s. The initial focus

* Corresponding author. Tel.: + 44-1904-433779; fax: + 44-1904-433759.
E-mail address: pcs1@york.ac.uk (P.C. Smith).

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was on the application of SD to management issues, but was soon extended to the analysis of environmental, social and macro-economic problems (Forrester, 1961, 1968, 1971). Roberts (1984) contains a collection of early papers. Since the mid-eighties, there has been renewed interest in applying SD to business policy and strategy problems. This interest has been facilitated by the availability of new, user friendly, high level graphical simulation programs (such as *ithink*, *Powersim* and *Vensim*). Easily accessible books describing the SD approach (for example, Senge, 1991; Morecroft and Sterman, 1994; Sterman, 2000) have also played a key role.

The SD methodology is consistent with traditional economic approaches towards modelling dynamic phenomena, but uses different conventions and terminology. The feedback structure of a system is described using causal loops. These are either *balancing* (capturing negative feedback) or *reinforcing* (capturing positive feedback). A balancing loop exhibits goal seeking behaviour: after a disturbance, the system seeks to return to an equilibrium situation (conforming to the economic notion of a stable equilibrium). In a reinforcing loop an initial disturbance leads to further change, suggesting the presence of an unstable equilibrium.

This structure is formalised via a simulation model consisting of two components: the stock and flow network, and the information network. Stocks capture the inertia of a system. They accumulate or deplete gradually, regulated by their in- and out-flows. Stocks can be ‘hard’ (tangible) concepts, such as physical capital, or ‘soft’ concepts (such as perceptions). The flow rates are determined by the information network, and depend on the level of the various stocks in the system. These rates can be interpreted as the output of policies, or decision making processes. For instance, in this paper one stock represents the number of hospital beds allocated to elective surgery. The in- and out-flows represent changes in this allocation, which are based on various information sources, such as the present number of beds, the expected waiting time for surgery, demands for non-surgical health care, and so on.

Mathematically, of course, such relationships can be modelled using systems of ordinary differential or difference equations, as in conventional dynamic economic models. However, the rapid advances in software technology make it possible readily to construct such SD models, and to test out a variety of alternative specifications. In particular, the purpose of this paper is to show how it has become possible to integrate conventional micro-economic models into the SD framework in order to offer readily accessible guidance to policy makers on the dynamic implications of economic models. The key insight into the economic models offered by this approach is that it yields numerical estimates of the *paths* taken by key policy variables, as well as any equilibrium to which they might converge.

2. A systems dynamics model of waiting time in the NHS

We illustrate the principles using the econometric model developed by Martin and Smith (1999), which is based on the static equilibrium models developed by Lindsay and Feigenbaum (1984), Cullis and Jones (1986) and Goddard et al. (1995). This literature examines the long waiting times for elective surgery that exist in some systems of health care, and recognises that such waiting time effectively acts as a 'price' for patients seeking health care free at the point of consumption. Within this framework, Martin and Smith develop separate econometric models of the demand for and supply of facilities for routine non-emergency surgery in the UK National Health Service (NHS). Demand for surgery depends on local waiting times, clinical need, the provision of family practitioner services and the availability of private health care. The supply of surgical capacity within the NHS depends on the total budget available to local managers (as proxied by hospital beds) and the local waiting time.

Using conventional econometric methodology, Martin and Smith estimated a model using cross-sectional data from over 4000 small areas in England. The result was a system of equations, of which the most important were the following:

$$\begin{aligned}\text{Demand} = {} & -\underset{(0.044)}{1.248} - \underset{(0.027)}{0.206}\,\text{'Wait time'} \\ & + \underset{(0.024)}{0.740}\,\text{'Need'} - \underset{(0.012)}{0.084}\,\text{'Family Practitioners'},\end{aligned}$$

$$\text{Supply} = \underset{0.042}{0.236} + \underset{(0.416)}{2.933}\,\text{'Wait time'} + \underset{(0.101)}{0.760}\,\text{'Beds'}$$

Logarithms were taken of all variables, so the coefficients can be interpreted as elasticities.

Solving these equations suggested that a (permanent) increase in health care resources would eventually result in reductions in waiting times without stimulating a large concomitant increase in demand. The study therefore offered useful policy guidance on the long-run equilibrium implications for waiting times and resource use of an increase in the health care budget, but begged a number of questions which the econometric analysis was ill-equipped to address. The most pressing of these is: bearing in mind the manifest rigidities in the system, how long would it take for the impact of increased resources to be fully reflected in reduced waiting time? Addressing this concern (and many other associated issues) requires consideration of a complex dynamic system of cause and effect. The SD methodology seeks to model each of the causal links explicitly, and to track the resulting system behaviour over time. We illustrate with the software package *ithink*.

Martin and Smith deployed a traditional static econometric approach assuming equilibrium conditions. This raises the issue of whether their elasticity estimates are valid inputs for a dynamic model. We therefore undertook further econometric analysis which allowed the elasticities to vary depending on the magnitude of the stock variables. We argue that, while the use of such methods may not be a perfect solution, in the absence of dynamic econometric evidence it is a significant improvement over the assumption of (say) a constant elasticity.

The stock, flow and information network of the model we choose to illustrate is shown in Fig. 1. There are five stocks, indicated by rectangles. Three of these (number of people on the waiting list, number of beds and expressed demand) are tangible quantities. (In the remainder of this paper, 'demand' refers to expressed demand, unless mentioned otherwise.) The remaining two (waiting time as perceived by the patient and general practitioner on the demand side, and waiting time as perceived by hospital management on the supply side) represent perceptions, and seek to capture how the two main actors adjust their perception of average waiting time over time as new information becomes available. In- and out-flows are represented by double arrows. The white head represents the direction of flow. For instance, when 'change in demand' is positive, demand increases, while if 'change in demand' is negative, demand decreases. Note that some flows are uniflows, e.g. 'patients treated' is always non-negative.

The stock 'Waiting list' is replenished by the flow 'Referrals' and depleted by the flow 'Patients treated'. The rate of referrals is determined by the level of expressed demand (calculated as patients per month). The number of patients treated per month depends on the number of beds, and the average length of stay. The stocks 'Demand' and 'Beds' are affected by the flows 'Change in Demand' and 'Change in Beds', respectively. The change in beds is driven by the elasticity of beds with respect to average waiting time as perceived by the supply side. The Martin and Smith (1999) study yields an elasticity estimate with respect to waiting time of 0.29. This reflects the internal pressures on allocation of resources between elective surgery and other forms of care. Change in demand is driven by the elasticity of demand with respect to average waiting time as perceived by the demand side. The econometric estimates indicate that the elasticity is not significantly different from zero for average waiting times up to about 3 months. It then decreases quite sharply, to reach a value of about -4.0 for waiting times of 4–5 months. Estimates for longer waiting times are less reliable due to the scarcity of data, but indications are that the value returns to zero. The perceived waiting time is modelled as a process of partial adjustment, where the perceived value is only gradually brought into line with the actual value. Mathematically, the perceived waiting time is a simple smoothed average of the waiting time with smoothing constant 1/'Time to perceive waiting time'. We set the 'Time to average waiting time' equal to one month for

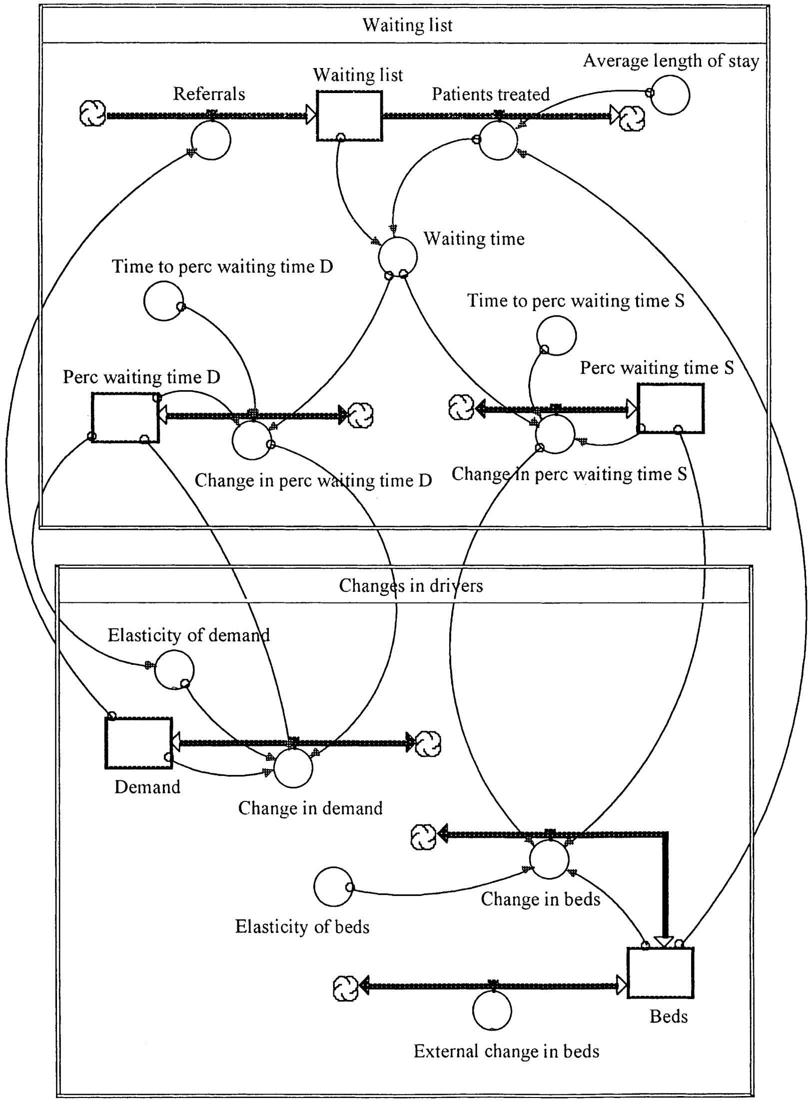

Fig. 1.

the supply side, and 12 months for the demand side, reflecting the more informed perceptions of the supply side. Appendix A lists the illustrative equations we have chosen for this demonstration of the full model, using a mixture of evidence and judgement.

3. Some illustrative results

We consider four scenarios, as summarized in Table 1. There are two initial equilibria, with respectively a 3 month and 4.5 month average waiting time. We then consider the impact of two alternative shocks taking place in month 10 of the simulation: a 10% increase in NHS resources and a 10% decrease. These are modelled using the 'External change in beds' flow. All simulations are run for 60 months. Fig. 2 illustrates the dynamic impact of these shocks on four variables: average waiting time, waiting list, NHS beds devoted to elective surgery and demand. We assume unchanging efficiency, as reflected in the 'Average length of stay', so the number of patients treated is a constant multiple of the number of beds. Further work might consider making efficiency endogenous.

Scenarios 1 and 3 have an initial average waiting time of 3 months, implying an elasticity of demand close to zero. The results are as expected. An increase in resources (Scenario 1) leads to a gradual decrease in both average waiting time and waiting list (Figs. 2(a) and (b)), there is no impact on demand (Fig. 2(d)) and the additional resources are gradually diverted from elective surgery to other purposes (Fig. 2(c)). A decrease in resources (Scenario 3) results initially in longer waiting times and lists (Figs. 2(a) and (b)), creating pressure to re-allocate beds to elective surgery (Fig. 2(c)). With some delay, a decrease in demand is observed (Fig. 2(d)), leading to a reduction of waiting time and waiting lists. The system stabilises at a new equilibrium with somewhat longer waiting time and waiting list, and slightly lower demand.

Scenarios 2 and 4 have an initial waiting time of 4.5 months, which implies an initially high demand elasticity. In Scenario 2 the sudden increase in resources results in an immediate shortening of the waiting time and list (Figs. 2(a) and (b)). The decrease in waiting time leads to some of the additional beds being reallocated to other areas (Fig. 2(c)), but also to a sharp increase in demand (Fig. 2(d)). This causes waiting times and waiting lists to increase, and the lost beds reverting back to elective surgery. About a year after the increase in resources (around month 24) the picture looks bleak: waiting lists reach a peak of 500 (i.e. a more than 10% increase, Fig. 2(a)) and waiting time is slightly higher than at the start of the simulation (Fig. 2(b)). Demand, having reached a high of about

Table 1
Overview of scenarios

	Initial waiting time	Resource change in month 10
Scenario 1	3 months	10% increase
Scenario 2	4.5 months	10% increase
Scenario 3	3 months	10% decrease
Scenario 4	4.5 months	10% decrease

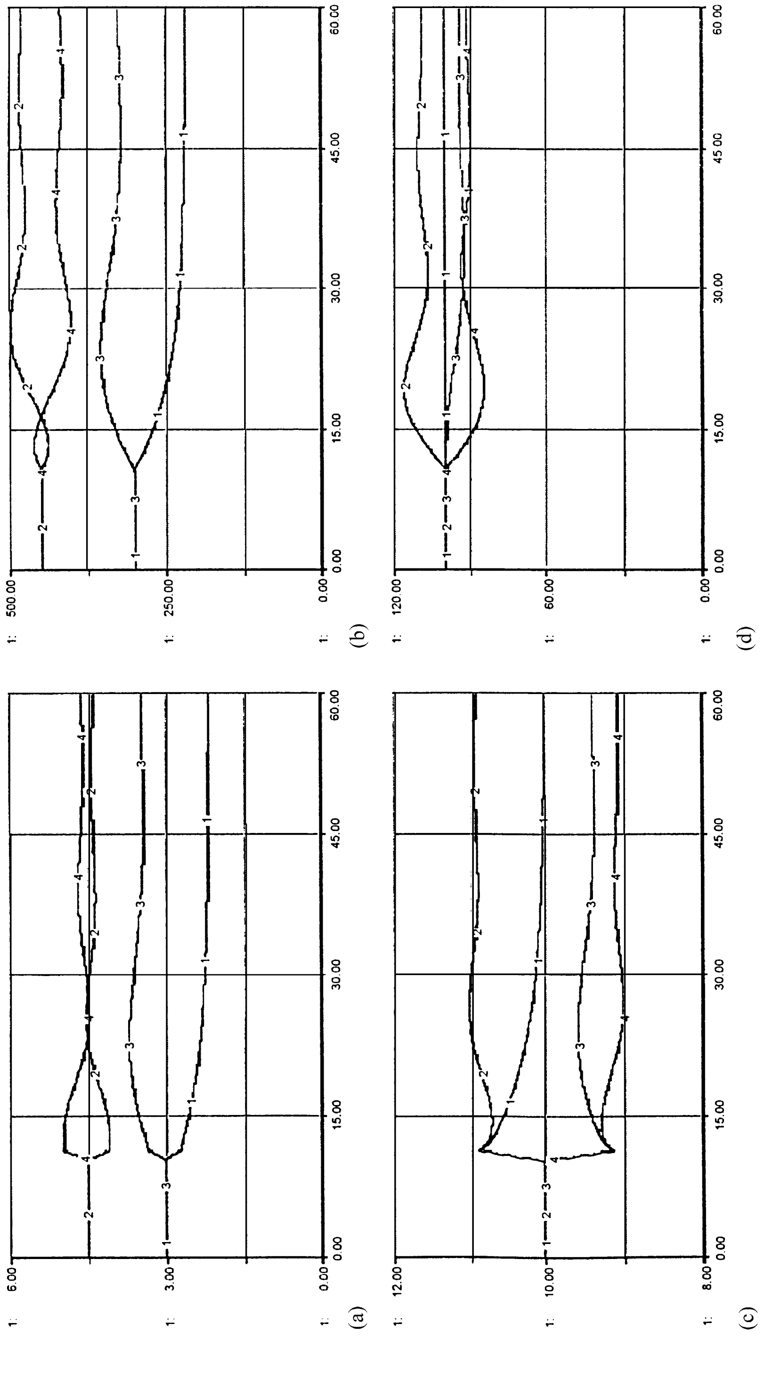

Fig. 2. Simulation results: (a) Waiting times; (b) waiting lists; (c) beds and (d) demand.

115 (a 15% increase, Fig. 2(c)), is on a downward trend. This implies that significantly more people are being treated than initially, but they have to wait longer. As the dust settles (about 2 years after the change) demand is approximately 10% above the initial level (i.e. part of the suppressed demand has surfaced), elective surgery has managed to hold on to its increased resources, waiting lists are longer by about 5% (despite the increase in resources!), while the average waiting time is marginally shorter. Here it is worth emphasising that in this scenario, one year after the resource increase, the situation actually looks worse, both in terms of waiting time and waiting list. From a political point of view, this may be a highly undesirable situation. While the resulting equilibrium is attractive (more people treated and lower average waiting time), this 'worse before better' path may be problematic. This result vividly illustrates the virtue of examining the dynamic implications of a policy shift within a SD framework.

In Scenario 4 the sudden decrease in resources results almost in a mirror image of Scenario 2: the increase in waiting time (and list) leads to a significant reduction in demand (i.e. demand is being suppressed), while elective surgery initially recovers some of its lost resources (Fig. 2(c)). But the decrease in demand pushes waiting lists and time down, and so the regained resources are lost. When the dust settles, demand is about 10% below the initial level, elective surgery has been unable to make up for the lost resources, waiting lists are about 5% shorter, while waiting time is marginally longer.

4. Discussion

This paper has demonstrated how it is possible to embed a simple static economic model within a dynamic framework using the systems dynamics methodology. In the absence of adequate data — particularly as regards the formation of perceptions — several assumptions had to be made. However it is a trivial matter to test alternative specifications within the SD framework. Indeed its strength is that it readily permits examination of a wide range of alternative models and scenarios. Combined with the readily accessible visual presentation of the paths taken by policy variables, we believe that judicious integration of economic and SD methodologies is likely to enhance the policy impact of both methodologies.

Appendix A. Specification of the dynamic model

Sector 1: Waiting list:

$\text{Waiting\_list}(t) = \text{Waiting\_list}(t - \mathrm{d}t) + (\text{Referrals} - \text{Patients\_treated}) * \mathrm{d}t$

INIT $\text{Waiting\_list} = 450$ {patients}

INFLOWS: Referrals = Demand {patients per month}

OUTFLOWS: Patients_treated = Beds/Average_length_of_stay {patients per month}
Perc_waiting_time_$D(t)$
$= $ Perc_waiting_time_$D(t - \mathrm{d}t)$ + (Change_in_perc_waiting_time_D) $*$ dt
INIT Perc_waiting_time_D = Waiting_list/Patients_treated {months}
INFLOWS: Change_in_perc_waiting_time_D = (Waiting_time_Perc_waiting_time_D)
/Time_to_perc_waiting_time_D {months per month}
Perc_waiting_time_$S(t)$
$= $ Perc_waiting_time_$S(t - \mathrm{d}t)$ + (Change_in_perc_waiting_time_S) $*$ dt
INIT Perc_waiting_time_S = Waiting_list/Patients_treated {months}
INFLOWS: Change_in_perc_waiting_time_S = (Waiting_time-Perc_waiting_time_S)
/Time_to_perc_waiting_time_S {months per month}
Average_length_of_stay = .1 {months}, Waiting_time = Waiting_list/Patients_treated {months}
Time_to_perc_waiting_time_D = 12 {months}, Time_to_perc_waiting_time_S = 1 {months}

Sector 2: Changes in drivers:
Beds(t) = Beds($t - \mathrm{d}t$) + (Change_in_beds + External_change_in_beds) $*$ dt
INIT Beds = 10 {beds}
INFLOWS: Change_in_beds = Elasticity_of_beds $*$ Beds $*$ Change_in_perc_waiting_time_S
/Perc_waiting_time_S {beds per month}
External_change_in_beds = GRAPH(Time)
{Used to model the resource changes in the various scenarios}
Demand(t) = Demand($t - \mathrm{d}t$) + (Change_in_demand) $*$ dt
INIT Demand = 100 {patients per month}
INFLOWS: Change_in_demand = Elasticity_of_demand $*$ Demand
$*$ Change_in_perc_waiting_time_D/Perc_waiting_time_D {people per month}
Elasticity_of_beds = .29 {constant}
Elasticity_of_demand = GRAPH(Perc_waiting_time_D)
(0.00, 0.00), (0.5, 0.00), (1.00, 0.00), (1.50, 0.00), (2.00, 0.00), (2.50, 0.00),
(3.00, 0.00), (3.50, $-$0.975), (4.00, $-$4.00), (4.50, $-$4.00), (5.00, $-$4.00),
(5.50, $-$0.975), (6.00, 0.00)

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