

# GENERAL FRAME OF RESOURCES, STRUCTURE AND TRADE-OFF

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System Dynamics explores the use of scarce resources to achieve some goals in a feed-back and possible feed-forward framework. Information (including orders), material, human resources, fixed capital and money have been the resources to choose from. Information network, however, should always be included in an SD model.

Besides information there is still another resource of an integrating nature — time. Scarcity and uncertainty are properties related to time. When scarcity of time is less critical than scarcity of products, for example, a trade-off in materials network between time and goods is economically meaningful: products can be manufactured to inventory before they are needed. Uncertainty about the future could make this choice too risky, however, although it might be acceptable in a more controlled situation.

All resources can be traded-off as they are to some extent alternatives to each other. The concept of trade-off rests on the idea of alternative costs and applies both to hardware and software systems (14).

Every simplification implies assumptions. Exclusion of time as a resource leads to the assumption that the only thing a modeller can do is to explore beforehand theoretically and/or by simulating, what should be done. This world-view leads to a min/max strategy that is behind the concept of robustness: the model should work properly even when there is gross uncertainty about the future and/or the model itself. This means, however, that new information about the nature of uncertainty remains untouched. In Bayesian terms, ex-ante information is being used, but ex-post information disregarded.

It has been hypothesized that environmental turbulence will be growing (1). If this happens, the cost of unused information will increase in the future.

It is easy to construct an SD model in which a sales forecast is added to utilise ex-ante and ex-post information. This kind of construction does not convert time to an explicit resource, however, as future uncertainty has not been treated as a trade-off variable.

Suppose now that time has been selected as a resource. Time is now an explicit variable which transforms the effects of future uncertainty to some common terms, used by all resources. Not before that can the trade-off problem be solved.

From time viewpoint information has two dimensions: ex-ante and ex-post. Future is unknown in each ex-ante situation but nevertheless the model builder looks ahead into the future a group of time units, called collectively planning horizon. In ex-post phase the modeller is, for some time, satisfied with

only that information he receives from the true state of the world. That slice of time is called time-increment.

It is not meaningful to proceed without planning. Therefore, planning horizon and time increment are related in the following way:

$$\text{time increment} \leq \text{planning horizon} \leq \text{run-length}$$

Run-length is a kind of land mark that fixes the time frame. Both other aspects of time are actually variables but in a research framework a kind of comparative static approach is useful: they are treated as parameters which vary from run to run depending on the experimental setting used.

A norm (or goal) is needed for guidance in the trade-off process in order to find common terms for all resources. In traditional SD modelling this norm is implicit and deduced from the pattern of believed ideal relationships of the time-series. As system structure is the main determinant of system behaviour in feed-back and feed-forward models, model builders try to improve it from run to run. The structure is fixed within each run, however, as there is no over-all goal available at that moment of time. On the other hand, system structure can be made variable by including an explicit objective function to the model and optimizing or quasi-optimizing the function during the run. If the model structure has been selected as a variable it increases reaction speed and therefore might buffer from shocks.

Feed-back models can be quite robust to forecast errors but major surprises certainly require very strong adaptive mechanisms, like explicit use of model structure. By moving in two-dimensional space of the time-resource it should be possible to avoid time-variable combinations which are sensitive to major surprises or catastrophes. If that does not succeed, it is not likely that anything could have been done better with other tools either.

Fixed model structure transforms into a variable one when optimization by repetitive simulation using artificial parameter-variables is being used (8). Translated to SD terms it means that some rate equations will be changed by changing heuristically some optimization algorithm variables, which simultaneously define some rate equations as parameters.

It seems likely that the very concept of optimization is going to change when the real possibilities of computers have been accepted. Currently system dynamicists principally use computers only as extremely rapid calculators of routine work. The situation is basically the same as that prevailing in administrative EDP-applications field in the early sixties. SD models have already been used to generate synthetic data from the "real world" (13) but a further step is also possible: let the model generate data that are needed to build or change the same model, and by using an objective function to guide

the process (9)

Generally speaking, this leads to the extended SD methodology to the group of model generators. This area is going to be of growing importance because

- (a) design effectiveness relative to competing methodologies (like LP) improves. Improvements in this respect are valuable to SD because structure-oriented modelling methods are apt to be tailor-made by their very nature.
- (b) group decision-making is likely to be the mode of management behaviour in the future (7). Therefore, a methodology will be required which gives an integrating framework to controversial interpretations of the real world as it is or should be.

The comments above refer primarily to the ordinary model building stage. More or less automatic use of structural changes, when actually running the model, means however that the model itself is going to correct its functioning and, therefore, the model will be a model generator on continuous basis.

Structural changes are of two types, depending upon the totality of the change: relative or absolute. Relative change means that some rate equations change during the simulation run but information network remains unchanged. Change is absolute when also information network changes. This occurs because at least one rate-defining parameter receives a value of 0 and thus eliminates some link connection in information network.

Optimization can be made by changing the model structure during the run-length or without doing it. To distinguish between these two cases, expressions 'dynamic' and 'static' optimization will be used. Because of extra freedom gained by a variable model structure, dynamic optimization should give better results than that for static optimization. Reverse situation indicates only that the surveillance function of time-related trade-off procedure has failed.

The idea of structural changes can be utilized in many situations, for example, in corporate modelling, in theory formation in business economics, in estimating the value of information currently or suggested, and in communication theory.

Lack of SD paradigm elasticity regarding disaggregation is a well-known handicap. Expressed in more general terms it means that SD is not especially suited for purpose where different hierarchical levels should be integrated into the same model. This problem is not constrained only to system structure, however, as every system consists also of goals and actions. An SD model describes just one hierarchical surface and cannot therefore include the over-all goal of the next higher level, unless an objective function has been included. This is because all policy corrections are implicit transformations of the higher level deviation.

Thus far it has been assumed that structural changes are time-related, i.e. are effects of structural changes in the real world.

However, structural changes can also be triggered from technical reasons as model size might require decomposition procedures at a specific time (4), (9). From model behaviour viewpoint there is no distinction between both cases.

To summarize: the general approach outlined above requires three extensions to traditional SD modelling practices; optimization, structural changes and inclusion of time as a resource. The new elements interact with each other and the old ones as follows:

Unknown future is being evaluated with ex-ante and ex-post information, using all resources to estimate proper reactions. It is the function of variable model structure to generate the over-all response required, using objective function.

The value of objective function, received from an optimization process and combined with free judgement of the modeller(s), is a changing norm because aspiration level of the modeller fluctuates. Just in this area the old but recently revitalized Behavioral Theory of the Firm (1), (12) and SD meet each other.

Changes in parameter-variable values overtake the role of real variable changes in SD simulation. As a result, freedom of the interactive modeller increases because his decisions can now be based on three kinds of information:

- (a) improvements in objective function values
- (b) parameter-variable values and value changes
- (c) time series of ordinary model variables

#### Earlier research related to the general frame

A Dynamo-based optimizing version SDRDYN was developed at the Helsinki School of Economics in 1976. Its use (8), applications based on static optimization (3), (8), (9) or dynamic optimization under certainty (2), (10) have been reported elsewhere.

In summer 1979 a new project was started, first to install Dysmap to the HP-3000 computer at the Helsinki School of Economics, and then to add to Dysmap new properties in order to increase internal decision-making of the Dysmap-language, and in the way the user decides. At the beginning of February Dysmap version currently available allows the user

- (a) to optimize heuristically through the SDR-algorithm
- (b) to optimize unlimited number of objective functions (one at a time), using unlimited number of parameter-variables, without translating the model again
- (c) to simulate, to optimize without structural changes, or to optimize with structural changes either in absolute or relative sense
- (d) to use ex-ante and ex-post information as alternatives which the computer automatically recognizes via a special parameter, KEY. The main rule is

that Dysmap treats KEY as zero unless the modeller has not given it any other value. For the time-increment phase, however, KEY is internally interpreted having a value of one. Planning and doing can thus be programmed into the same equation.

#### An application of the general frame

To test the frame the first time the model should simultaneously be realistic and simple. Therefore, a real-life demand curve was adapted from Coyle (5) and added to the well-known Production-distribution Case from the Jarman's Problem Book. A classical control engineering solution (Jarman's alternative) static optimization solution and dynamic optimization solution were then compared by using as the yardstick a combined objective function that had worked well before (8). This function minimizes the cumulative cost of retail inventory, inventory change, and production change. If the new frame is valid, dynamic optimization should give best results.

Those equations which are new or modified have been listed below:

C KEY=0

A  $FCST.K = (1 + BIAS * (1 - KEY)) * TABHL(TDMD, TIME.K +$

X  $(1 - KEY) * M1, 0, 100, 10)$

R RS.KL=FCST.K

T  $TDMD = 75/85/120/95/110/105/100/95/90/82.5/75$

C M1=4

C BIAS=0.4

NOTE EQUATION FOR RETAIL ORDERS

R  $RO.KL = M2 * ARS.K + (1 - M2) * FCST.K + A1 * (B1 * RIDC + B2 * RID.K - RI.K)$

X  $/TAI + A2 * ((C1 * DRO + C2 * D DR.K) * (M2 + ARS.K + (1 - M2) * FCST.K)$

X  $-FOB.K)/TAPL$

C M2=1

Other Definitions:

KEY = The internal switch parameter

FCST = Sales Forecast

BIAS = Forecast Bias factor

M1 = The weight given to the forecast four months from now

M2 = The weight given to average sales

RS = Retail sales

RO = Retail orders

A1,A2,B1,B2,C1,C2 = Decision parameters  
(=parameter-variables)

Figure 1 below shows the experimental setting used in the study:

	TIME INCREMENT				
	20	30	40	60	120
P L A N N. H O R. .	20				
	30				
	40				
	60			Not Available	
	120				

Figure 1: Planning horizon/time increment combination used for the study of 120 period run-length

Parameter-variables had the following upper and lower bounds:

$$\begin{array}{ll}
 0 \leq A1 \leq 1 & 0 \leq C1 \leq 1 \\
 0 \leq A2 \leq 1 & 0 \leq C2 \leq 1 \\
 0 \leq B1 \leq 1 & 1 \leq M1 \leq 10 \\
 0 \leq B2 \leq 1 & 0 \leq M2 \leq 0
 \end{array}$$

The step size of the SDR-algorithm was 0.2 and the number of iterations used was 30.

Fig. 2 collects results from the study into a three-dimensional map where axes measure relative values of time. The ratio of cumulative costs from each experiment to cumulate costs from static optimization indicates the goodness of each experiment in cost terms. The ratios show the height of the relative-cost mountain at specific points. The value of point (1,1) is 1 and it derives from the definitions used.

Saw-tooth pattern of demand causes extra costs, if planning horizon interferes with that pattern, although there is over-all decreasing cost trend when time-increment and/or planning horizon is shortened. The smallest value of both parameters (=20 weeks) increases costs significantly as the model has now become "shortsighted". The message of Fig. 2 is, however, that it is easy to improve static optimization by structural changes at least in this specific case.

#### Detailed analysis of optimizing behavior

Let us select from Fig. 2 the best value (0.62), the poorest value (3.15) and the reference value (1.00) for a closer study. Table 1 collects for each case parameter values and cumulative costs of the "real world" run (with KEY=1).

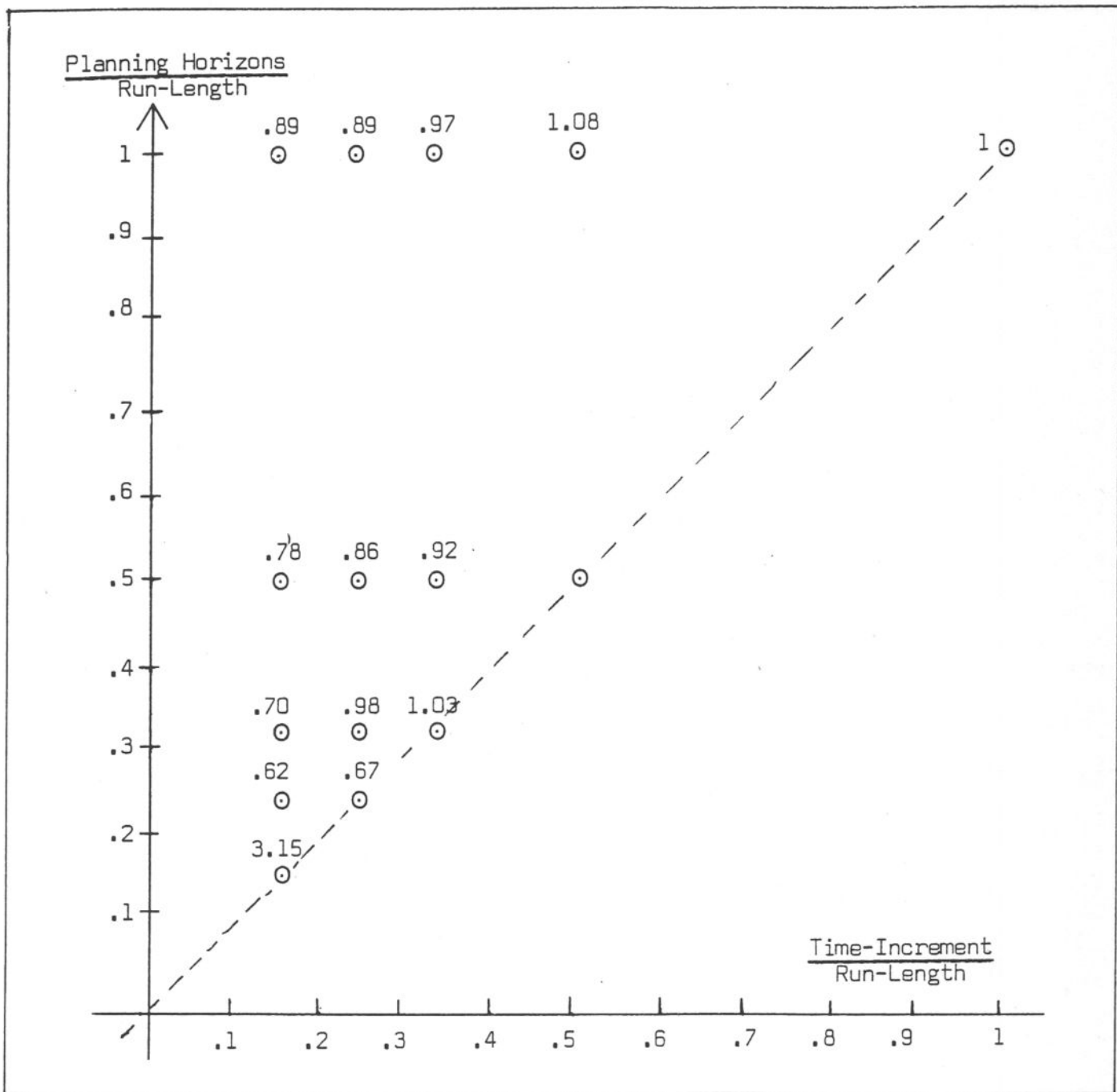


Figure 2: Comparison of dynamic optimization runs with the static run when forecast bias is 0.4

The upper portion of Table 1 gives information from the run where planning horizon was 30 weeks and time-increment 20 weeks. In the poorest run both parameters were 20 weeks. Comparison of parameter-variable data in Table 1 shows that the best and the worst run differ especially regarding the values given to parameters A1, A2 and B1. There is remarkable difference in the smoothness of parameter value corrections between both runs. If the planning-horizon/time-increment combination has been poorly selected, parameter response is

too heavy. Structure-driven behaviour of ordinary SD models has now been transferred to parameters because of extra freedom given to the system by structural changes. This phenomenon can be seen clearly from Fig. 3, which shows the values of A1 as a function of A1-changing iterations (=efficient iterations). The vertical lines indicate the point (after 30 iterations) where new structure was selected for the coming 20 time periods.

Time	0-20	21-40	41-60	61-80	81-100	101-120
A1	0.4	0.2	0.3	0.08	0.06	0.06
A2	1	1	0.825	0.845	0.865	0.885
B1	1	0.98	0.805	0.825	0.845	0.825
B2	0.084	0.324	0	0.2	0.67	0.65
C1	0.912	0.892	0.902	0.902	0.902	0.902
C2	0.004	0.024	0	0	0	0
M1	4.792	8.752	9.562	9.922	9.922	9.922
M2	0	0.24	0.17	0.15	0.13	0.11
Cumul. cost ( $\times 10^6$ )	0.100	0.155	0.169	0.175	0.179	0.180
A1	0.912	0	0.375	0	0.02	0.02
A2	0.288	1	0.97	0.99	0.99	0.99
B1	0.998	0.51	0.135	0.115	0.535	0.135
B2	0	0.004	0.014	0.214	0.414	0.214
C1	0.712	0.796	0.886	0.906	0.926	0.926
C2	0	0.084	0.086	0.066	0.066	0.066
M1	1	7.372	10	10	10	6.4
M2	0.252	0	0	0	0	0
Cumul. cost ( $\times 10^6$ )	0.603	0.725	0.793	0.853	0.892	0.910
A1	0.4					
A2	0.728					
B1	0.912					
B2	0.084					
C1	0.912					
C2	0.084					
M1	3.784					
M2	0.936					
Cumul. cost ( $\times 10^6$ )	0.289					

TABLE 1. Comparison of three optimization solutions



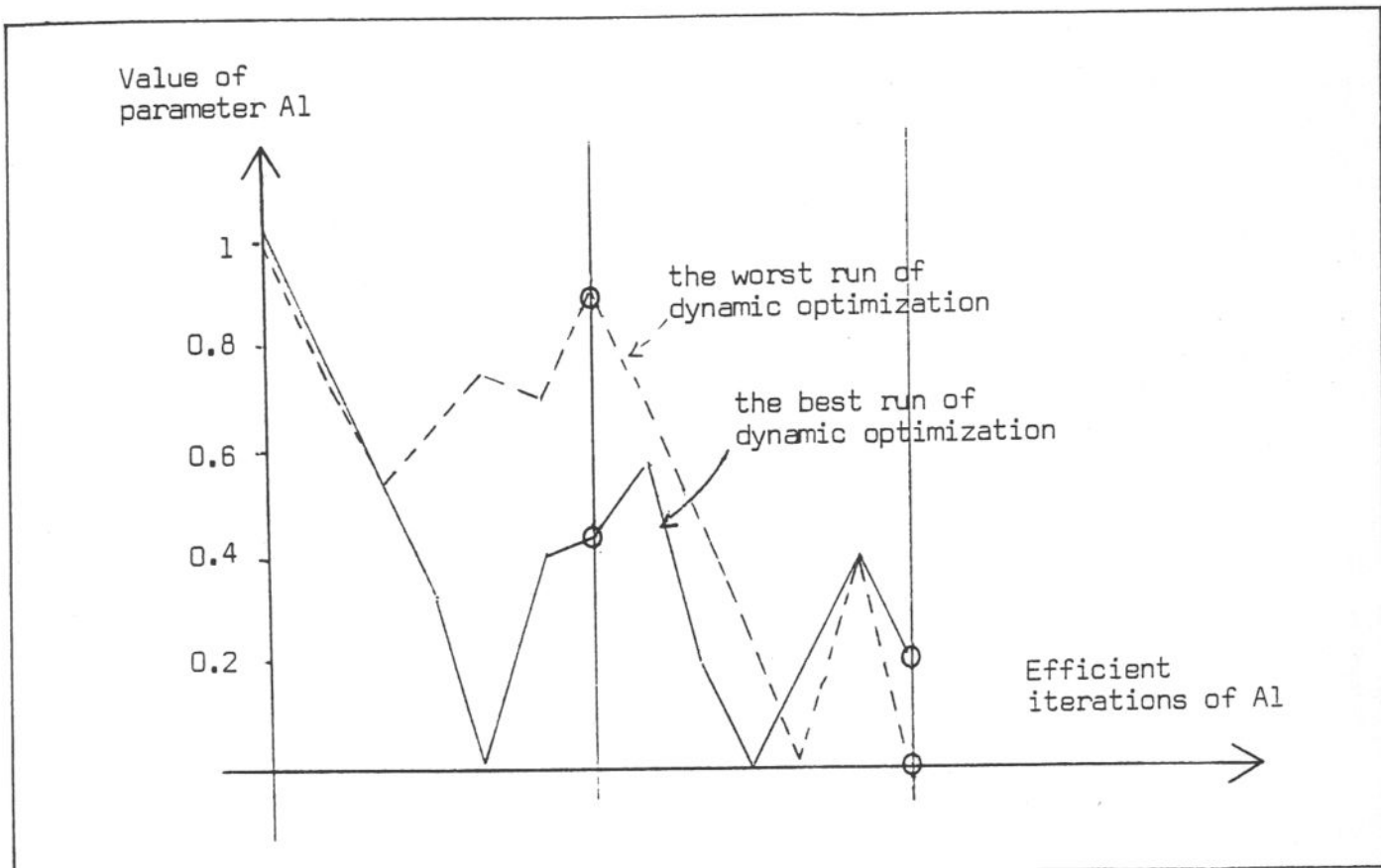


Figure 3: Historical values of A1 in efficient iterations

The case of the best run was optimized once more, but now by "rounding" to zero all those parameter-variables that had final values less than arbitrarily selected 0.1, each time when

structural changes were made. Table 2 summarizes new solutions thus received. The value of this modified model in relative cost terms is 0.67, which is still way below 1 of the static optimization model.

Time	0-20	21-40	41-60	61-80	81-100	101-120
A1	0.4	0.2	0	0	0	0.270
A2	1	1	0.530	1	1	1
B1	1	0.980	0.710	0.135	0.115	0.135
B2	0	0.440	0.710	0.135	0.535	0.535
C1	0.912	0.892	0.912	0.922	0.942	0.942
C2	0	0	0	0	0	0
M1	4.792	8.752	8.932	9.742	9.922	9.292
M2	0	0.240	0.260	0.210	0	0
Cumul. cost ( $\times 10^6$ )	0.113	0.174	0.179	0.181	0.184	0.194

TABLE 2 The best run with absolute changes in structure

We had above an example of Dysmap working as a model generator, which produced 4 different models:

Time	0-20	21-40	41-60	61-80	81-100	101-120
Average Sales	x	x	x	x		
Inventory	x	x				x
Patterns of absolute change	-----		-----		-----	-----

We can now see that there are really three kinds of information use to choose from:

- (a) Constant use      information sources and information weighting remain constant
- (b) Mixed use        information sources remain constant but weighting varies because of relative changes in structure
- (c) Variable use     information sources and weighting vary because of absolute change(s) in the structure

In the experiment under discussion, variable use of information caused a slight cost increase but it might at the same time lead to "savings". For instance, it would motivate organizational units when they see that today the moral responsibility is at their hands. Perhaps management should inform people working in the inventory area that inventory size is so important that the control rule has switched the inventory information on again. In short, with decision rules using information rotation, employees might receive the same kind of vision enlargement in future than traditionally only a few people get with job rotation in management education.

Preliminary investigations indicate that dynamic optimization might not be too sensitive to moderate forecasting errors. Experiments with 30/30 combination of planning-horizon and time-increment gave the following results:

Bias	0	40%	60%	80%
Cost Ratio	0.59	0.67	0.59	1.35

It remains to be answered the question of how well the control theoretical simulation model of Jamain's alternative number 3 would do in cost terms when the test situation was the same as before. The reply is: not too well, as the costs were more than three times as high as in static optimization.

Let us finally look at time series received from the runs discussed before:

- (1) Simulation methodology (Jamain's No.3) - - Fig.4
- (2) Static optimization methodology (Reference Case) - - Fig. 5
- (3) Dynamic optimization methodology
  - (a) The best run (30/20) - - Fig. 6
  - (b) The worst run (20/20) - - Fig. 7

The following conclusions can be made:

- (A) All four pictures look different, which means that optimization process has pushed the models to really different real-world solutions
- (B) The simulation model of case (1) shows least stability. The situation might improve to some extent if a sales forecast were used. Anyhow, optimization gave better results
- (C) Optimization models should be evaluated in light of the objective function used. The function selected this time for study emphasized inventory size and inventory changes. There is no doubt that visual ranking of cases (2), (3a) and (3b) corresponds with the ranking received from the final values of the objective function used. This is encouraging as objectives are a central concept in modern business thinking, although the nature of the over-all criterion may vary, for instance, from cost minimization to profit, market share or ROI maximization.
- (D) The study confirms that combination of information uses, mentioned on this page, is useful for a modeller:
  - improvements in objective function value
  - parameter-variable values and value changes
  - time series of ordinary model variables

#### Final Comments

The Study has shown how the concepts of resources, structure and trade-off can be integrated into a bigger "whole". After all, this is not too surprising as Systems Thinking and System Dynamics are only two different domains of the same RAISON D'ETRE.

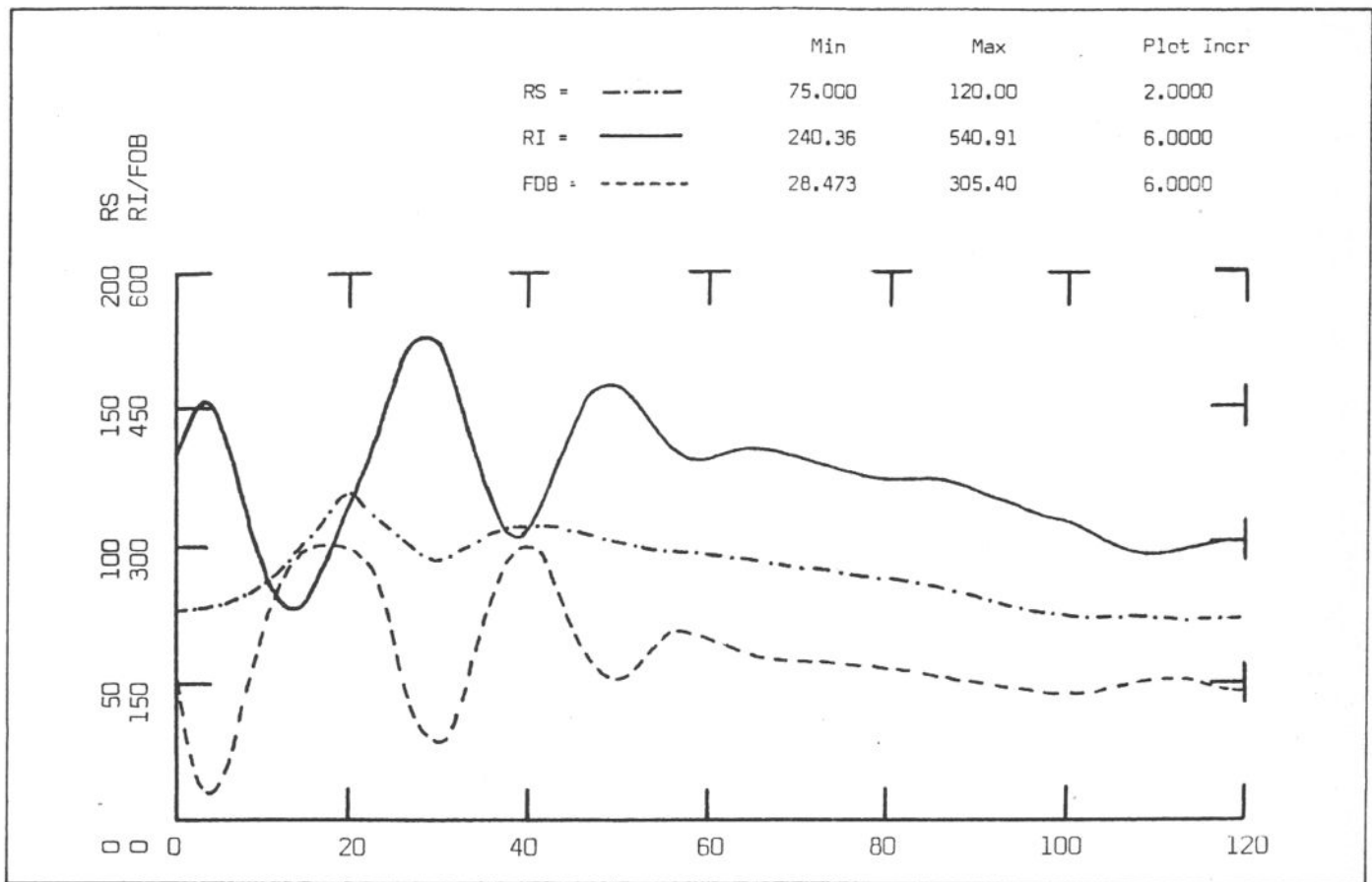


Figure 4: Simulation run model no. 3 from Jarman's

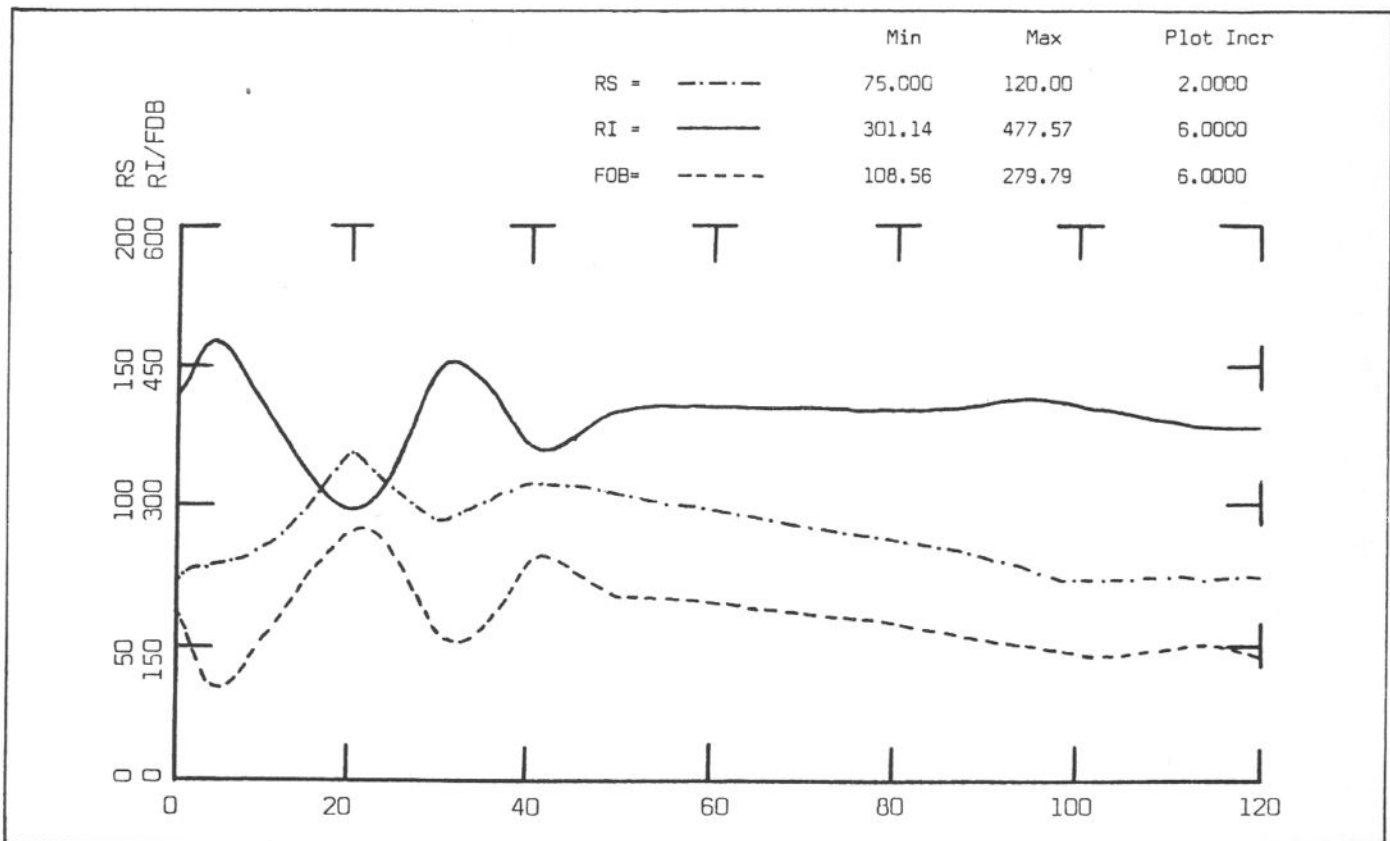


Figure 5: Static optimization run (The Reference Case)



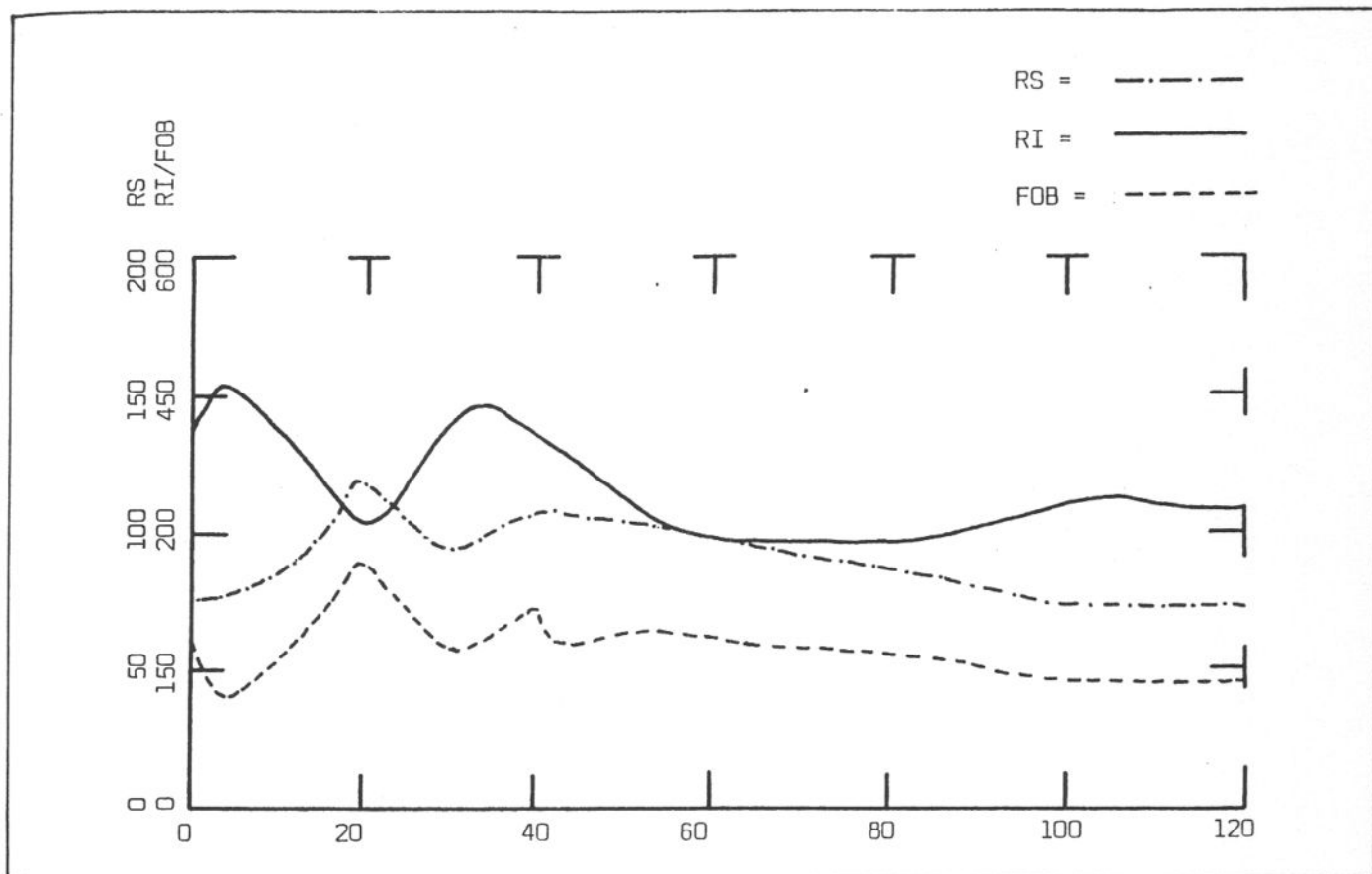


Figure 6: Dynamic optimization run (The Best Run)

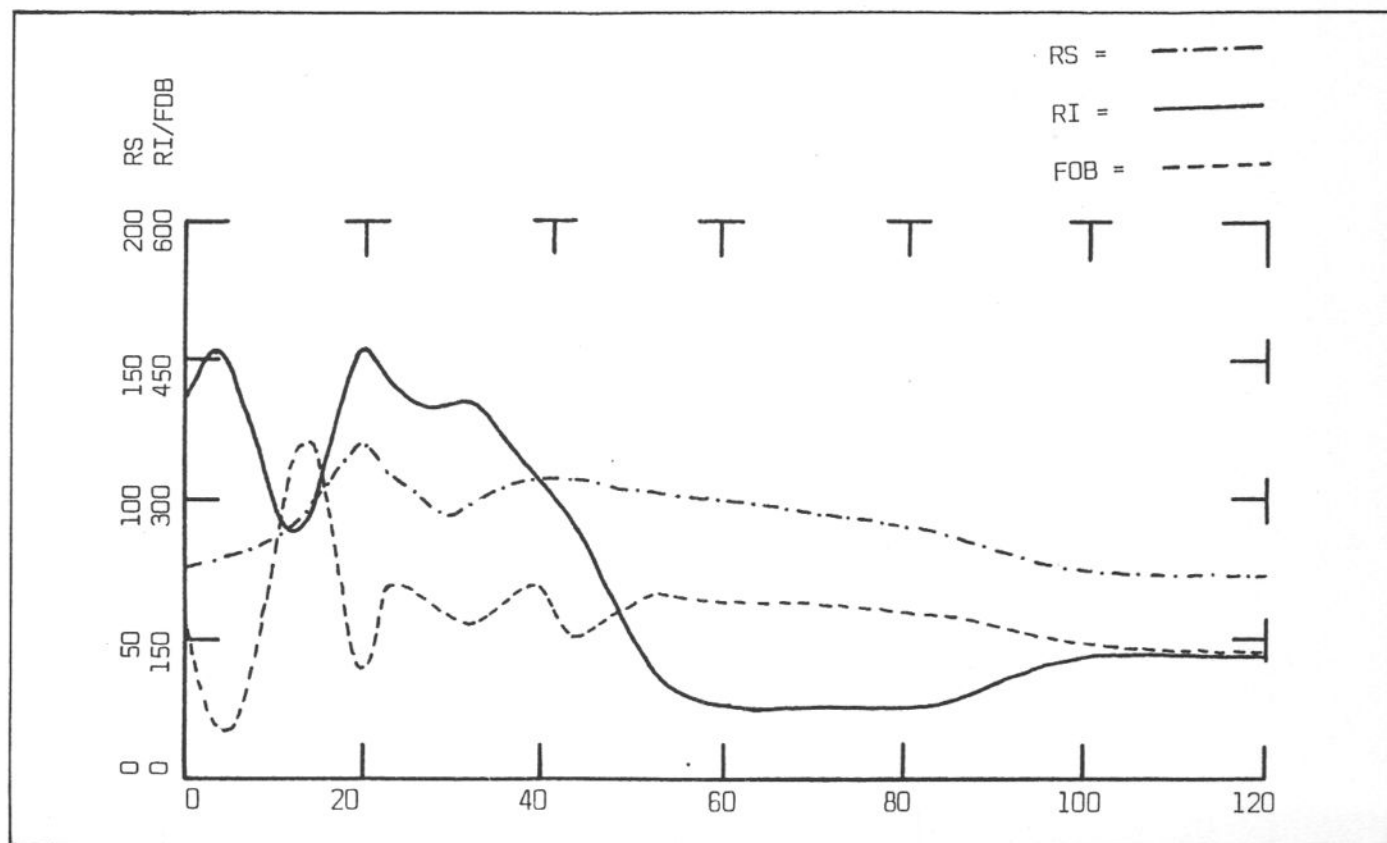


Figure 7: Dynamic optimization run (The Worst Run)

1	* PRODUCTION-DISTRIBUTION SYSTEM	
2	NOTE ORDINARY EQUATIONS	
3	L $RI.KL=RI.J+DT*(FP.JK-RS.JK)$	RETAIL INVENTORY
4	R $FP.KL=PA.K$	FACTORY PRODUCTION
5	L $PA.K=PA.J+DT*1/TAP*(PI.J-PA.J)$	PRODUCTION ABILITY
6	A $PI.K=FOB.K/WBD$	PRODUCTION INDICATED
7	L $FOB.K=FOB.J+DT*(RO.JK-FP.JK)$	FACTORY ORDER BACKLOG
8	L $ARS.K=ARS.J+DT*1/TARS*(RS.JK-ARS.J)$	AVERAGE RETAIL SALES
9	A $TRID.K=WAS*ARS.K$	TRIAL VALUE FOR RETAIL INV DESIRED
10	A $RID.K=MAX(TRID.K, TVRI.K)$	RETAIL INVENTORY DESIRED
11	A $TVRI.K=STEP(450, TTC)$	TERMINAL VALUE OF RETAIL SECTOR
12	C $TTC=1000$	TIME FOR TERMINAL CONSTANT
13	A $DDE.K=FOB.K/PA.K$	DELIVERY DELAY ESTIMATE
14	L $DDR.K=DDR.J+DT*1/TDDR*(DDE.J-DDR.J)$	DELIVERY DELAY RECOGNISED
15	A $PLD.K=(C1*DRO+C2*DDR.K)*ARS.K$	PIPELINE ORDERS DESIRED
16	C $K=0$	
17	A $FCST.K=(1+BIAS*(1-KEY))*TABHL(TDMD, TIME.K+$	
18	X $(1-KEY)*M1, 0, 100, 10)$	
19	R $RS.KL=FCST.K$	
20	T $TDMD=75/85/120/95/110/105/100/95/90/82.5/75$	
21	C $M1=4$	
22	C $BIAS=0.4$	
23	NOTE EQUATION FOR RETAIL ORDERS	
24	R $RO.KL=M2*ARS.K+(1-M2)*FCST.K+A1*(B1*RIDC+B2*RID.K.-RI.K)$	
25	X $/TAI+A2*((C1*DRO+C2*DDR.K)*(M2*ARS.K+(1-M2)*FCST.K)$	
26	X $-FOB.K)/TAPL$	
27	C $M2=1$	
28	NOTE DECISION PARAMETERS	
29	C $A1=1$	
30	C $A2=0$	
31	C $B1=1$	
32	C $B2=0$	
33	C $C1=1$	
34	C $C2=0$	
35	NOTE ORDINARY PARAMETERS	
36	C $TAP=4$	
37	C $WBD=2$	
38	C $TARS=1$	
39	C $RIDC=400$	RETAIL INVENTORY (IF A CONSTANT)
40	C $TAI=2$	TIME TO ADJUST INVENTORY
41	C $DRO=2$	DELAY IN RECEIVING ORDERS

42	C	TAPL=2	TIME TO ADJUST PIPELINE
43	C	WAS=4	WEEKS OF AVERAGE SALES
44	C	TDDR=2	TIME TO ADJUST DELIVERY DELAY RECOGNIZED
45		NOTE INITIAL EQUATIONS	
46	N	RI=400	
47	N	FOB=200	
48	N	PA=100	
49	N	ARS=100	
50	N	DDR=DDE	
51		NOTE ***** MULTI-OBJECTIVE PART OF THE MODEL *****	
52		NOTE CFPCO IS AN OBJECTIVE FUNCTION CANDIDATE	
53	L	$LFP.K = LFP.J + DT * (FP.JK - FPI.JK)$	
54	N	LFP=100	
55	R	$FPI.KL = LFP.K$	
56	A	$FPCHA.K = FP.JK - FPI.JK$	
57	A	$FPCOST.K = PARA1 * FPCHA.K * FPCHA.K$	FACTORY PROD COST
58	L	$CFPCO.K = CFPCO.J + DT * FPCOST.J$	CUMULATIVE FACTORY PROD COST
59	N	CFPCO=0	
60	C	PARA1=300	COST PARAMETER NUMBER ONE
61		NOTE CRICH IS AN OBJECTIVE FUNCTION CANDIDATE	
62	R	$RIR.KL = RI.K$	
63	L	$RIL.K = RIL.J + DT * (RIR.JK - RIL.J)$	
64	N	RIL=400	
65	A	$RICHA.K = RI.K - RIL.K$	
66	A	$RISCH.K = PARA2 * RICHA.K * RICHA.K$	
67	L	$CRICH.K = CRICH.J + DT * RISCH.J$	CUMULATIVE RETAIL INV COST
68	N	CRICH=0	
69	C	PARA2=3	COST PARAMETER NUMBER TWO
70		NOTE CRICO IS AN OBJECTIVE FUNCTION CANDIDATE	
71	A	$RICOST.K = PARA3 * (WAS * ARS.K - RI.K) * (WAS * ARS.K - RI.K)$	
72	L	$CRICO.K = CRICO.J + DT * RICOST.J$	CUMULATIVE RETAIL INV COST
73	N	CRICO=0	
74	C	PARA3=0.03	COST PARAMETER NUMBER THREE
75		NOTE DERIVED OBJECTIVE FUNCTION	
76	A	$OBJF.K = CFPCO.K + CRICH.K + CRICO.K$	
77		NOTE OUTPUT SPECIFICATIONS	
78		PRINT 1)RS,RO,RI,FOB,OBJF	
79		SPEC DT=1/LENGTH=23/PRTPER=1/PLTPER=0	
80		RUN	
81		+	

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