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THE SENGE ARCHETYPES: FROM CAUSAL LOOPS TO COMPUTER SIMULATION

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Abstract

This paper will examine a number of archetypes discussed in Senge's "The Fifth Discipline". In particular, it will use these models to demonstrate the nature of local learning and local rules. This will include a discussion of the relationship between learning and system equilibrium. In this process frequent comparison will be drawn between the relative merits of Causal Loop Diagramming and computer simulation.

The dynamics of the causal loops, already discussed by Senge, will be examined briefly. This will be followed by a discussion of the computer models of a number of archetypes and their dynamics. The mathematical logic of these models will be explained. The models will then be used to demonstrate how the phenomenon known as "Local Learning" is represented by a dissipative system that brings the organization or system back into a new state of equilibrium.

The paper seeks to demonstrate that computer simulation allows a level of analysis that provides a more complex comprehension than the simpler technology of Causal Loop Diagramming.

THE SENGE ARCHETYPES: FROM CAUSAL LOOPS TO COMPUTER SIMULATION

SIMULATION OF THE SENGE ARCHETYPES.

In the "Fifth Discipline", Senge (1992) outlines eight archetypes which he believes constitute consistent patterns of behaviour in organizations. These archetypes are widely and easily recognizable by anyone who has worked in a large and complex organization. Whether or not these archetypes are widespread and recurrent has not been verified by research nor has the validity of their structure and function been established at an empirical or theoretical level. This paper examines a number of archetypes at a theoretical level to throws light on their workings.

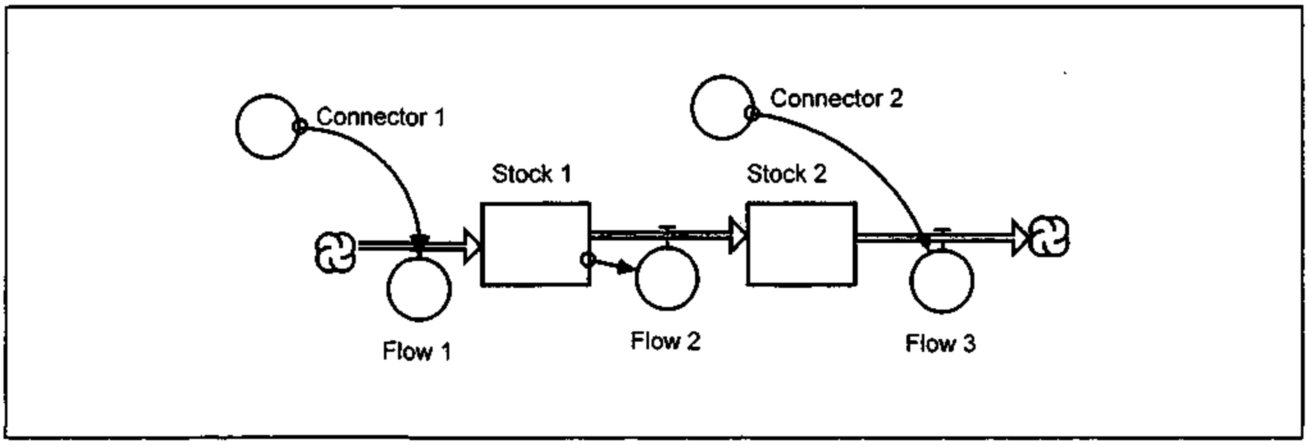
In this process the impact of local learning on system dynamics and the related question of the dynamics of dissipative systems are discussed as useful tools to an understanding of the Senge archetypes.

The analysis is done using a software modelling package which allows examination of the dynamics of the archetypes over time. It is the change from the relatively static perspective of the causal loop diagram to the dynamic perspective of the software model that the insights into the functioning of the archetypes emerges.

The Modelling Methodology.

The archetypes have been constructed using a software package developed by Barry Richmond of High Performance Systems. The package, called "iThink" or "Stella" uses a simple set of icons to represent stocks and allows equations to be entered to provide graphical output of the system. A simple system is seen in Fig.1

Fig.1: Simple "iThink" Model



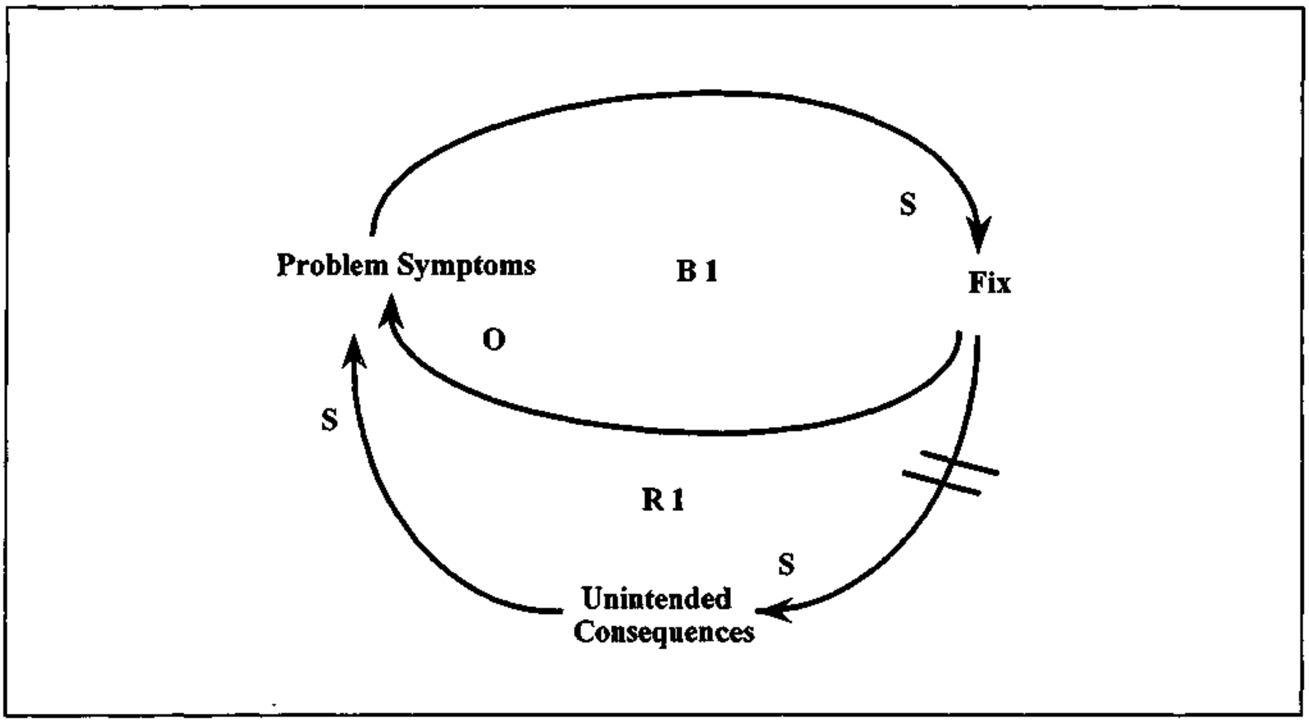
The Stocks represent accumulations which can vary over time. A bank account would be a simple stock. Flows represent inflows to stocks and outflows from stocks. An inflow to a bank account would be deposits and an outflow would be withdrawals. Converters are used to regulate the rates of flows such as the rate of deposits into the bank or the rate of withdrawal out of the bank. The thin lines between converters and flows are called connectors. While flows handle the movement of material which will increase with an inflow and decrease with an outflow, converters send information concerning rates. Where stocks and flows vary over time, a converter is not decreased by the operation connector. For example, a converter may be an interest rate. The operation of that interest rate over time does not, of itself, vary the interest rate.

In building simulations of the archetypes, each element of an archetype was built as a separate sub-system consisting of a single stock with an inflow and an outflow with converters which regulated the inflows and outflows.

The model Fixes that Fail is probably the simplest of the archetypes and will serve as an illustration of the method used. This archetype deals with the dynamics of a situation where the symptoms of a problem are dealt with rather than the underlying problem. The unintended consequence is development of another problem which exacerbates the original Problem Symptoms. It is also an example of the counter-intuitive nature of policy decisions where a policy designed to produce one outcome produces an unexpected and sometimes totally opposite outcome.

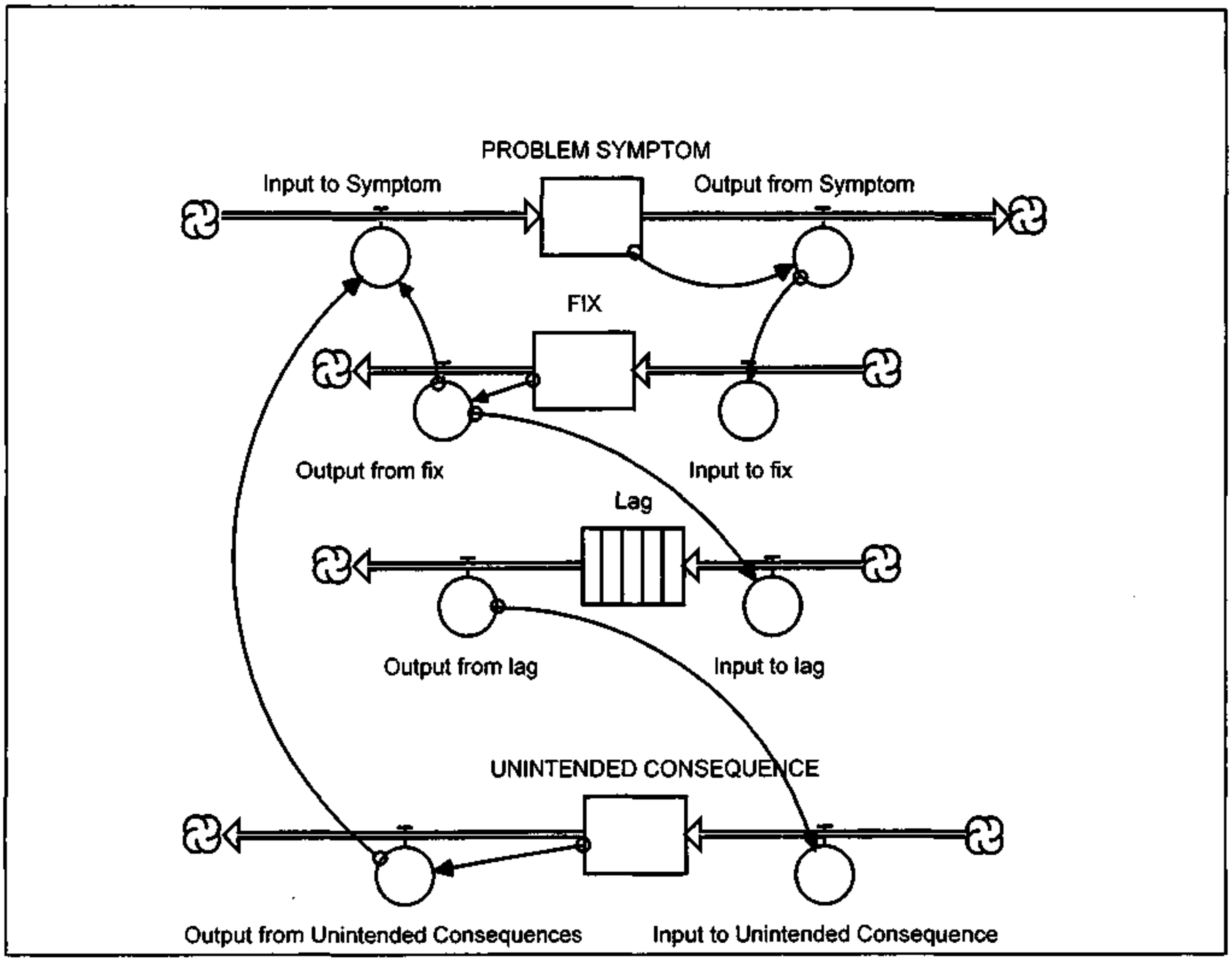
Thus while a causal loop model of Fixes that Fail would look like this:

Fig 2: Causal loop of Fixes that Fail.



An "iThink" model would look like this:

Fig 3: "iThink" model of Fixes that Fail



Each element of the model has an inflow and an outflow which allows it to vary over time. These variations are communicated to the other stocks through the converters. The lag in the Causal Loop is shown here as a Conveyor which works on the same principle as an conveyor belt.

In building the models a simple first approximation of the operation of each archetype was made. Any causal connection with an 'S' in the causal loop was seen as adding to the next stock and those with an 'O' in the causal lop were seen as subtracting. Thus a linear model of causation was proposed in the first instance. An example of the workings of this model is shown in the next two tables.

Operation of $\xrightarrow{S}$ Causation

Value of Output from Stock 1	Value of Input to Stock 2
2	2
1	1
0	0
-1	-1
-2	-2

Operation of —O→ Causation

Value of Output from Stock 1	Value of Input to Stock 2
2	-2
1	-1
0	0
-1	1
-2	2

Such an approach makes each stock of equal importance and later the impact of variation in the relative values of stocks will be discussed. In examining the impact of variations in the relative values of the stocks it necessary to discuss two related aspects of the dynamics of systems, local learning and dissipation.

Local Learning

Local learning occurs at a local level or within a local environment. It is not generalized in the way one might expect of organizational learning but is learning that occurs only where it is relevant. All sub-systems are engaged in local learning, a process which produces local rules which provide stability for the sub-system. The reason that the learning is local is that it emerges to suit the specific and special needs of a local sub-system. When the learning benefits a sub-system, namely provides an on-going level of stability, the local rules will persist. Essentially, the development of local rules from local learning constitutes behaviour that ensures the success or survival of the sub-system at its own local level. Whenever the locality is disturbed by a new input, or perturbation, from the environment, it adapts or learns a new set of coping behaviours that are designed to stabilize the local environment having come to terms with the new state of affairs.

This adaptation is performed, in systems terms, by negative feedback loops, or in causal loop terms, by balancing loops. These dissipative systems absorb the impact of the disturbance or perturbation and smooth it out. In effect, the system uses negative feedback as an adaptive or learning strategy. Thus the process of learning is the process of integration of a new input into a system to create a new equilibrium.

An example is where Police in a district find that there is an increase in car thefts during daylight hours. This constitutes a perturbation or changed input into their district. To combat this they increase mobile patrols during daylight hours. When they do this the car thefts decline, so the Police begin reducing the patrols. As they do this the car thefts begin to increase again. The situation continues to see-saw until a new balance of patrol intensity and car thefts is achieved. This is evidence of the development of a local rule, specific to this system, the car theft and prevention system, that has resulted from local learning. This learning is different from individual learning in that it is a systemic rather than an individual response to the situation.

Dissipation of Perturbation.

There are two important aspects of the archetypes that need emphasising. These are the actions of the balancing and re-inforcing loops. By far the most important of these for the sake of this discussion is the action of the balancing or negative feedback loop. Whereas the re-inforcing loops, designated by R in the causal loop diagrams drive the system either upwards or downwards, the actions of the balancing loops, designated B in the causal loops, act in quite a different way.

These loops serve to re-adjust the system to some form of input. They dissipate some form of perturbation or disturbance in the environment and as this happens the system adjusts to a new equilibrium state. In other words, it is the dissipative systems or negative feedback loops that enables the system to learn how to adjust to a new input. In other words, dissipating sub-systems allow the supra-system to re-adjust to a new system state that absorbs, compensates for, or learns to cope with the perturbation. The learning can be said to be complete when the system re-establishes equilibrium. This return to equilibrium can be seen clearly with he computer simulations of the archetypes however it cannot be demonstrated with the static causal loop technology.

In the computer simulation, the action of local learning which leads to new equilibrium states occurs in the equations that control the inflows and outflows to the stocks. It is the understanding of the mathematical relationships between the stocks as embodied in the inflow and outflow equations (or the causal links in the causal loop diagrams) that the importance of simulation modelling is understood To show dissipation at work, two archetypes will be discussed.

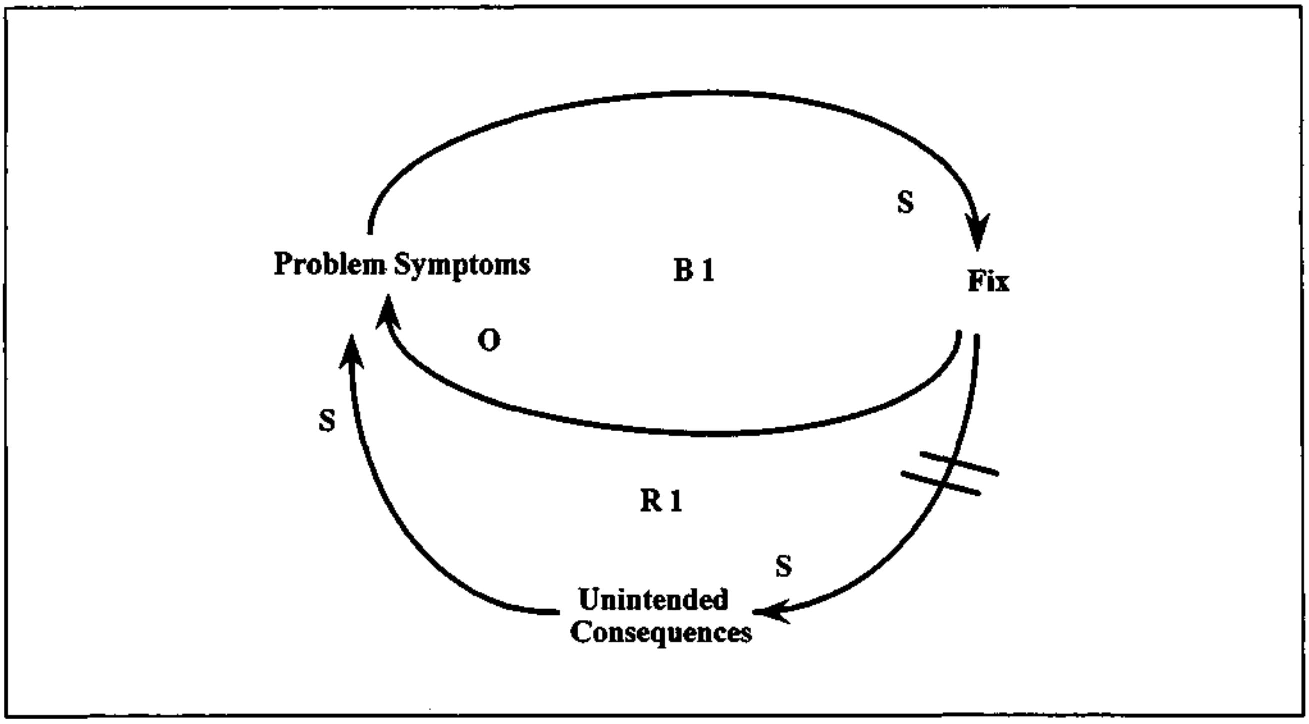
The first, "Fixes that Fail", is probably the simplest to understand. It is useful in this context because it comprises of only two loops, a balancing loop and a re-inforcing loop. While the impact of the re-inforcing loop is strong to begin with, it is the balancing loop that re-creates equilibrium.

The second, "Escalation", consists of two balancing loops. These serve to re-establish equilibrium. However, while the initial perturbation is as marked as in "Fixes", there does not appear to be a re-inforcing loop. It is important to notice that, it this case the two balancing loops act as a single re-inforcing loop. Thus the pattern of dissipation in both "Fixes" and "Escalation" is the same.

DISSIPATION (i): "FIXES THAT FAIL"

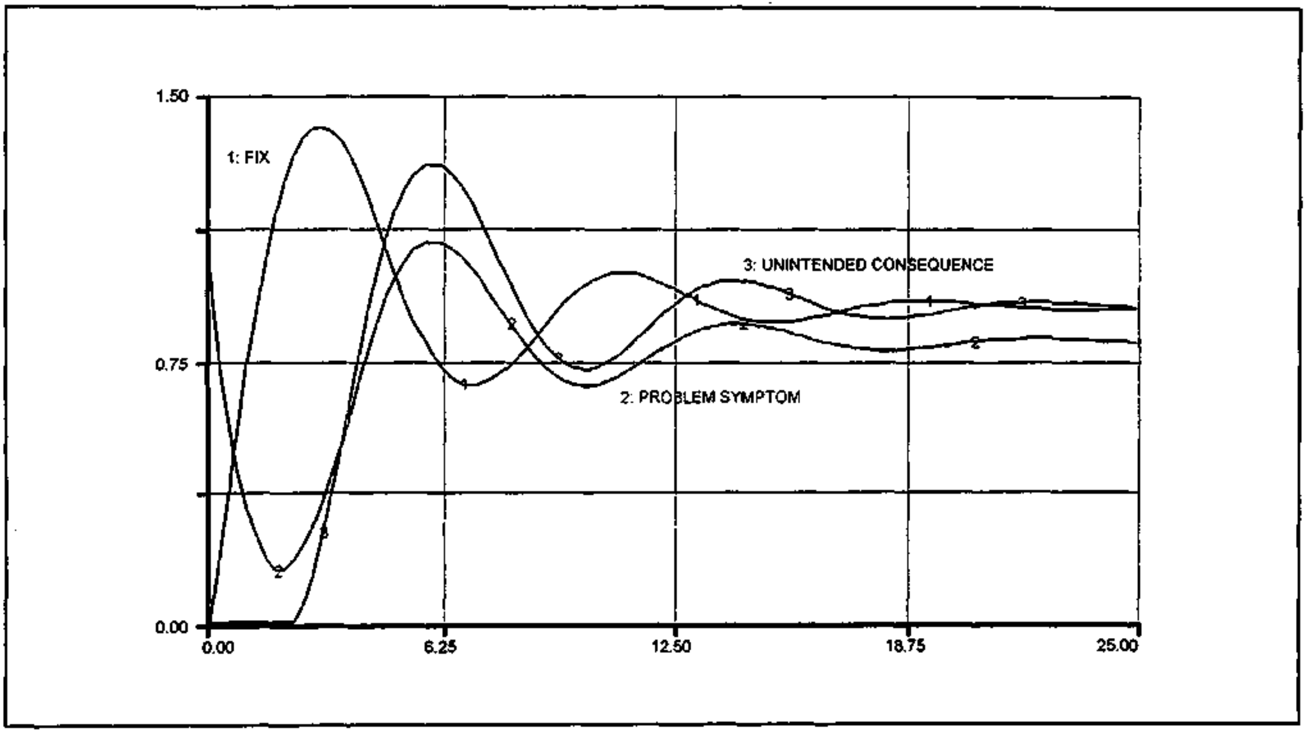
In the "Fixes that Fail" model shown below, the balancing loop B1 serves to bring the system back into a state of equilibrium. It is important to understand that a balancing loop does not return the system to its original state but seeks a new equilibrium in the system state that has been created by the re-inforcing loop R1.

Fig 4: Causal loop of Fixes that Fail.



The graphic output from this system shows how the problem symptom oscillates with the fix. The lagged effect of the fix produces an unintended consequence which oscillates as the fix itself oscillates. In this model, the system stabilizes at a new and higher equilibrium.

Fig 5: Graph of Fixes that Fail.



DISSIPATION (ii): "ESCALATION"

The second example is "Escalation" as seen in the escalation of the Arms Race during the Cold War. Any increase in the arms level of the Russians was met by an increase in the US arms level as the American tried to re-establish the original balance. This is the common response to threat where both sides have the ability to react to perceived threat. Some activity by one of the parties upsets the relative balance between two parties. Once this balance is shifted it affects the level of threat that one party perceives and that triggers a set of activities by that party that sets the system of escalation in motion again.

Fig 6: Causal loop of Escalation

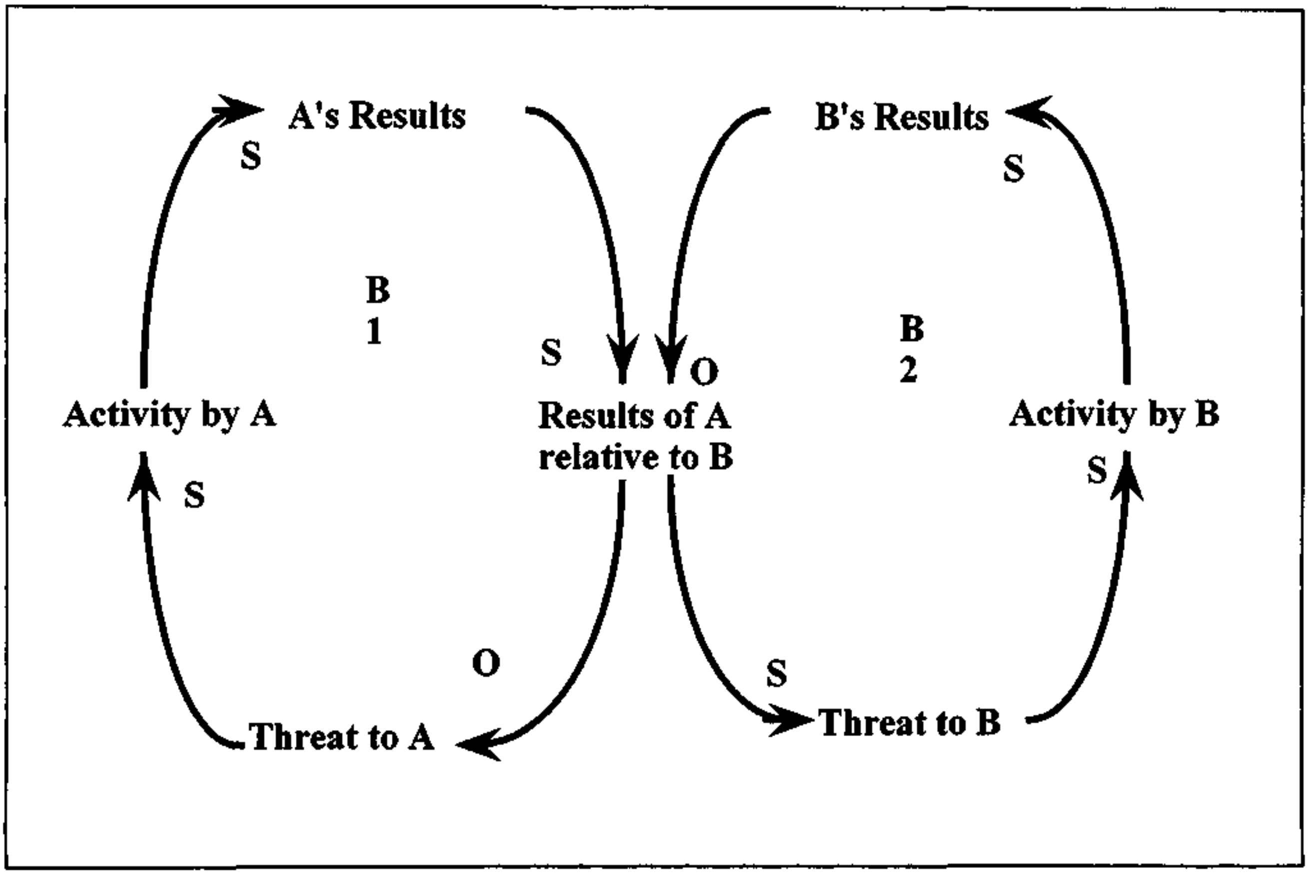
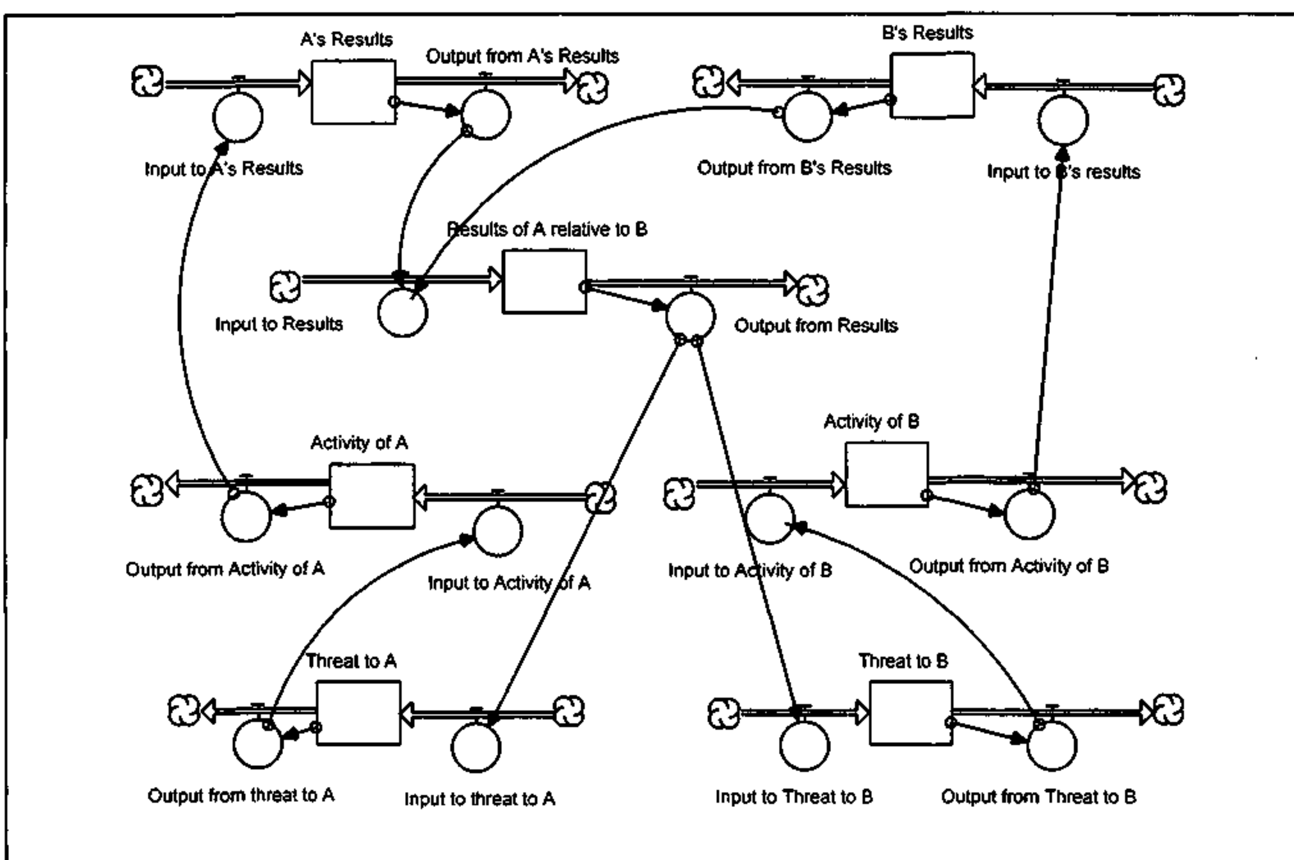
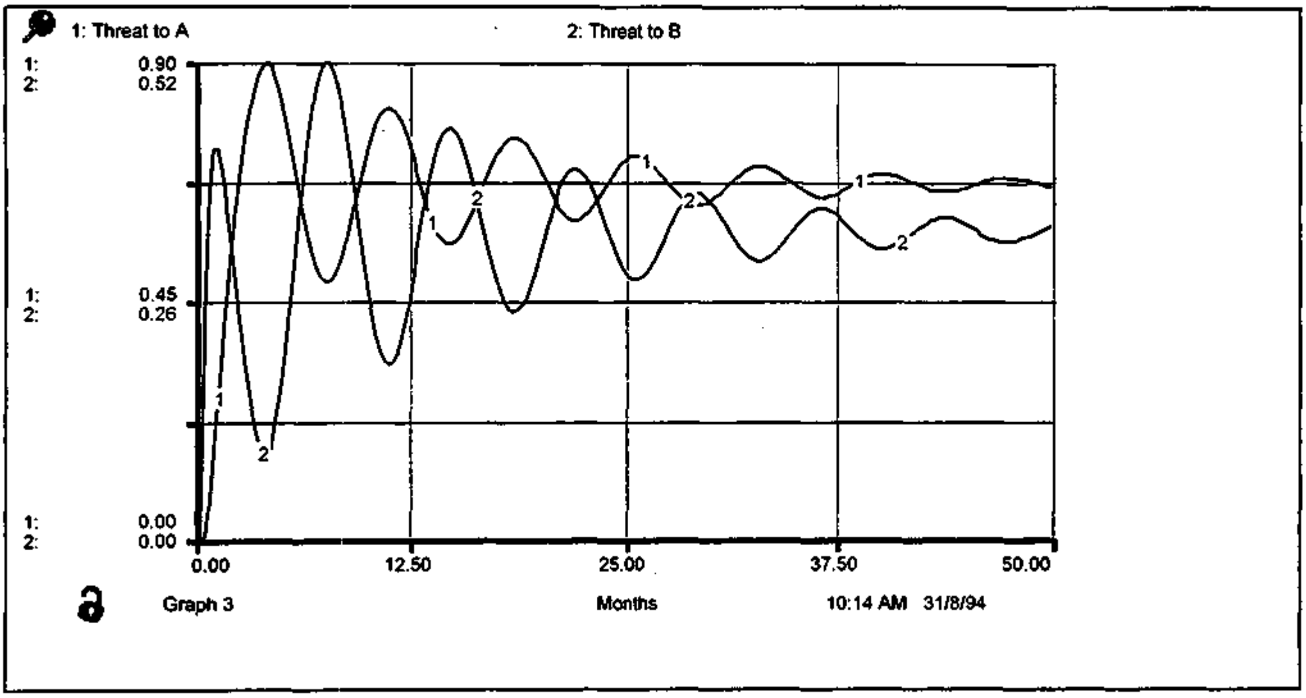


Fig 7: iThink model of Escalation.



Here the threat to the two parties oscillates until a new balance of terror is found. Whether or not the original arms ratio has been re-established or not is irrelevant. What has happened is that a new balance has been achieved at a higher level of armaments on both sides.

Fig 8: Graph of Escalation..



In the cases of both of these models, it is the presence of balancing loops embedded in the structure that produces this decreasing oscillation and equilibrium.

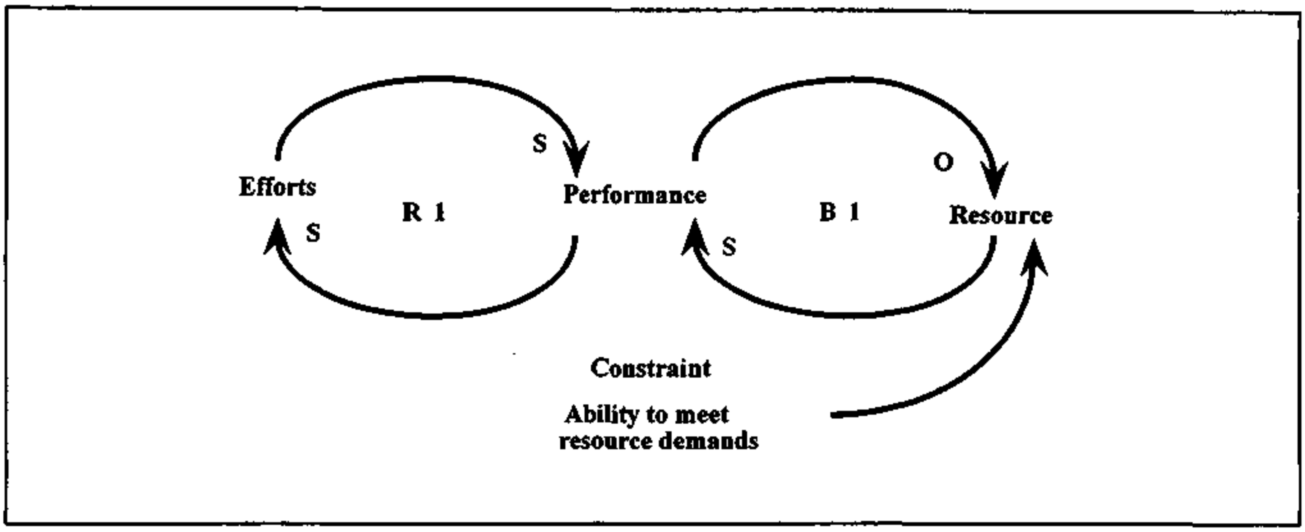
This is also a reflection of what we would expect instinctively, namely that systems tend towards stability after periods of fluctuation. In organizational systems there are many examples of organizations ability to respond to perturbation through the action of dissipative systems. In fact, it is the ability of organizations to produce stability and re-establish equilibrium through the dissipation of perturbation that enables them to survive.

In the next two sections the impact of local learning is examined in two archetypes, "Limits to Success and Growth" and "Shifting the Burden" In these archetypes the establishment of equilibrium is present as in the two earlier examples, however, in these case the impact of the local learning and local rules is examined and compared with the types of system state equilibrium that is re-established.

LOCAL LEARNING (i): LIMITS TO SUCCESS AND GROWTH.

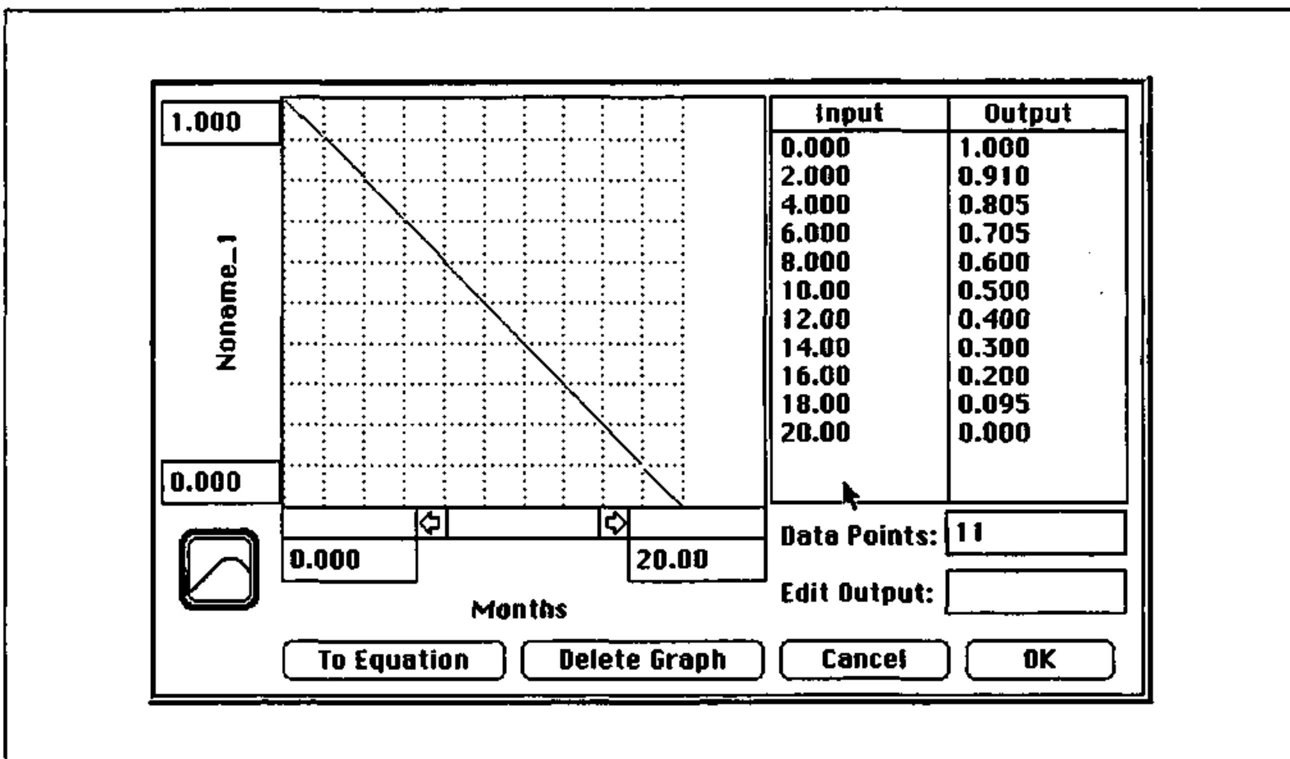
In this archetype there are three process at work. The first, in re-inforcing loop R1, is effort driving performance. An example is where advertising drives sales. The second process is in loop B2 where performance is balanced by a resource which is depleted by performance. As sales increase inventory declines. This decline is exacerbated by the third process a constraint on inventory. This may be the rate at which new stock can be obtained. This constraint leads to a decline in sales.

Fig 9: Causal Loop of Limits to Success and Growth



When constructing the computer simulation was built a converter was used for the constraint. The graphic function was set as follows showing a steady decline in the resource over time.

Fig 10: Graphical Input for Constraint



The model was programmed using the following logic.

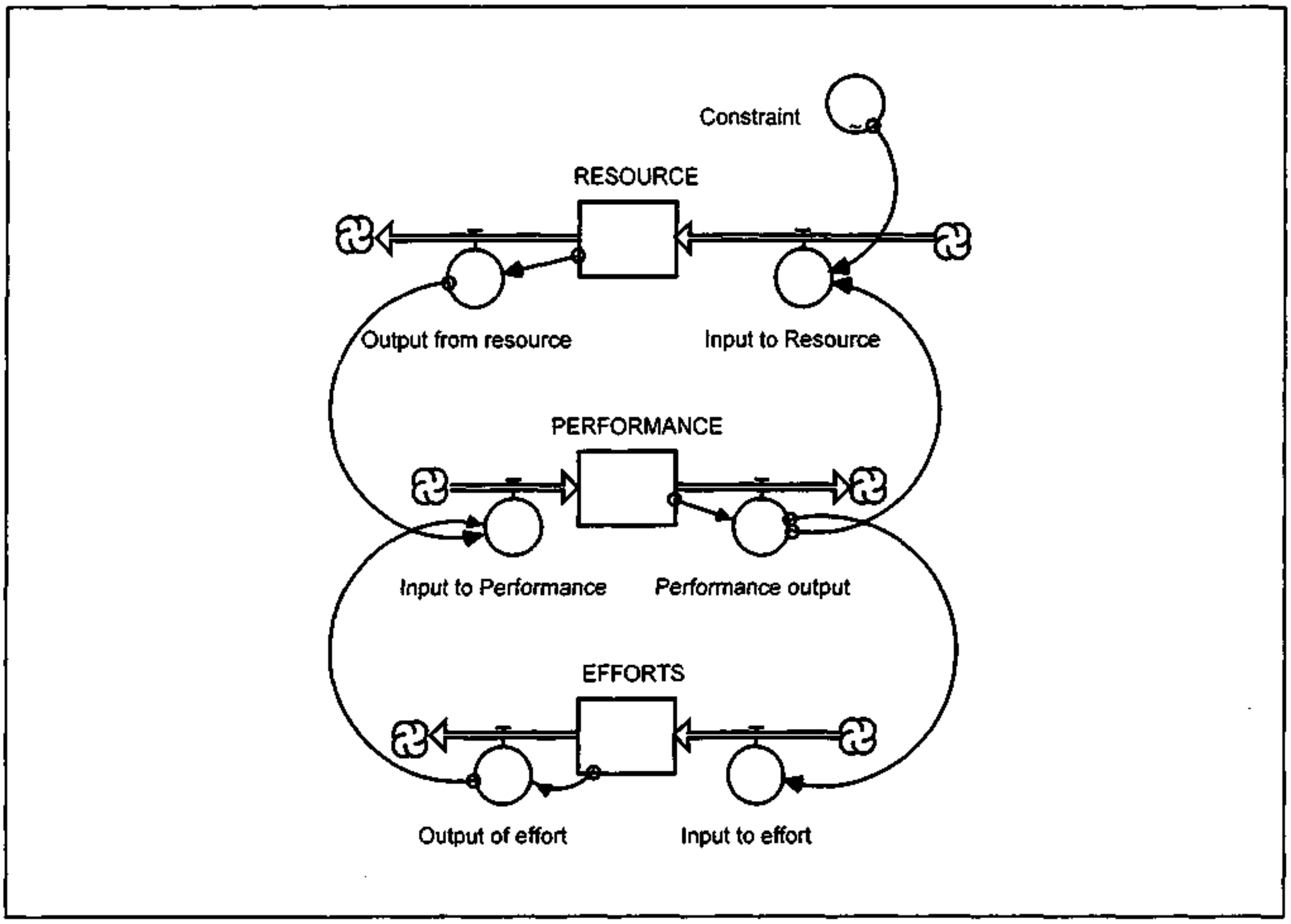
Performance = Resource + Efforts

Effort = Performance

Resource = Constraint - Performance

This indicates that performance is made up of the available resources plus the effort that is put in. The effort put in is driven by the performance that is achieved. In other words, if sales go up then the advertising campaign will either continue or increase. If sales decline, the advertising campaign will decline or be stopped. The iThink model looks as follows.

Fig 11: iThink model for Limits to Growth



The equations behind the model are.

EFFORTS(t) = EFFORTS(t - dt) + (Input_to_Effort - Output_from_Effort) * dt
INIT EFFORTS = 0
INFLOWS:
Input_to_Effort = (Output_from_Performance)
OUTFLOWS:
Output_from_Effort = EFFORTS

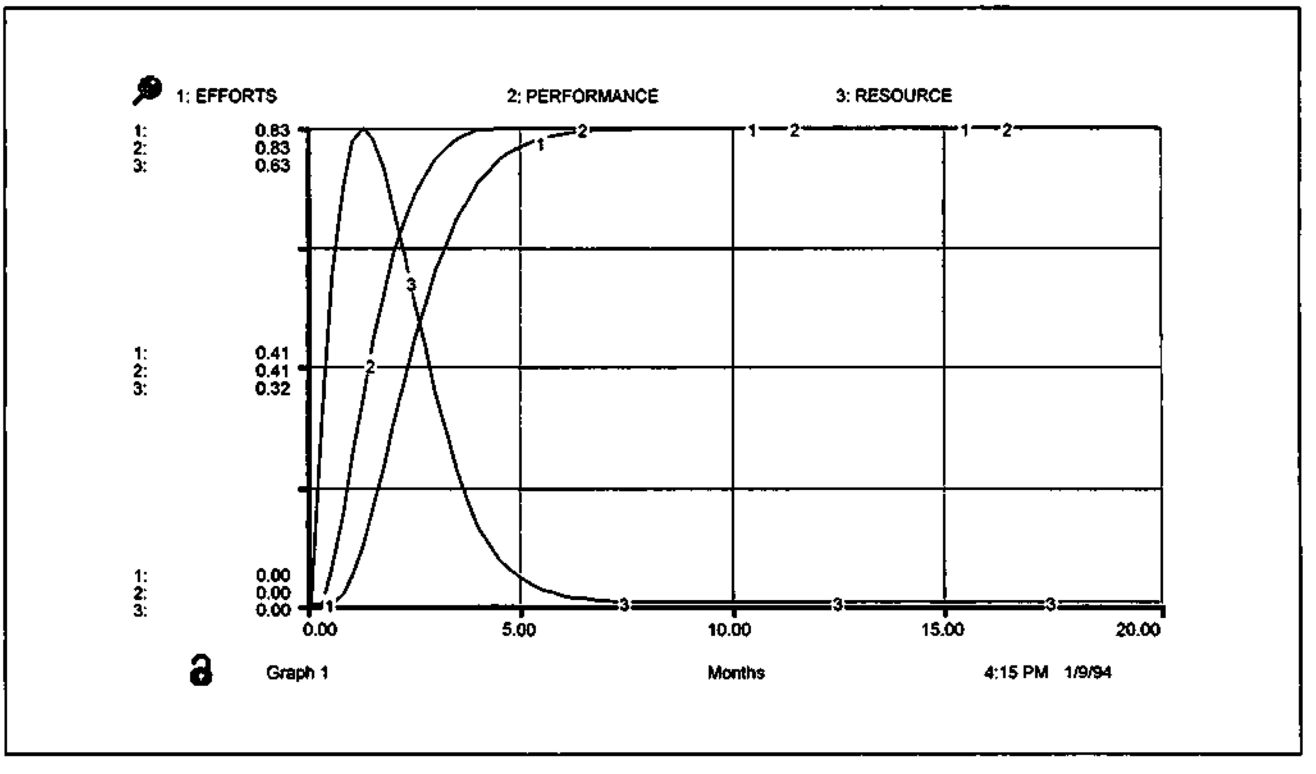
PERFORMANCE(t) = PERFORMANCE(t - dt) + (Input_to_Performance - Output_from_Performance) * dt
INIT PERFORMANCE = 0
INFLOWS:
Input_to_Performance = Output_from_Resource+Output_from_Effort
OUTFLOWS:
Output_from_Performance = PERFORMANCE

RESOURCE(t) = RESOURCE(t - dt) + (Input_to_Resource - Output_from_Resource) * dt
INIT RESOURCE = 0
INFLOWS:
Input_to_Resource = Constraint-Output_from_Performance
OUTFLOWS:
Output_from_Resource = RESOURCE

Constraint = GRAPH(TIME)
(0.00, 1.00), (2.00, 1.00), (4.00, 1.00), (6.00, 1.00), (8.00, 1.00), (10.0, 0.00), (12.0, 0.00), (14.0, 0.00), (16.0, 0.00), (18.0, 0.00), (20.0, 0.00)

The graph below shows that although Resource has declined to zero both effort and performance are maintained. This is clearly not the case as the resource is the key to continued Performance. Logic dictates that no matter how hard someone advertises, their ability to sell will go to zero once they run out of stock. Thus, it is clear that the model needs to reflect this fact by showing the relative importance of Resource over Effort.

Fig 12: Graph for Limits to Success (i)



While the simplicity of the causal loop diagram provides an important insight into the causal dynamics of this archetype, this simplicity can be seductively deceptive. Some thing more is needed to make this model work properly. There are some dynamics of the model that need to be attended to produce an accurate reflection of reality. This change needs to reflect dynamics at a more complex level that the Same/Opposite causal logic of the archetypes.

In the second simulation the fundamental logic has been changed. The relationship between Effort and Resource has been changed. Now the spending on advertising (Effort) is 50c for every $1 of Inventory (Resource).

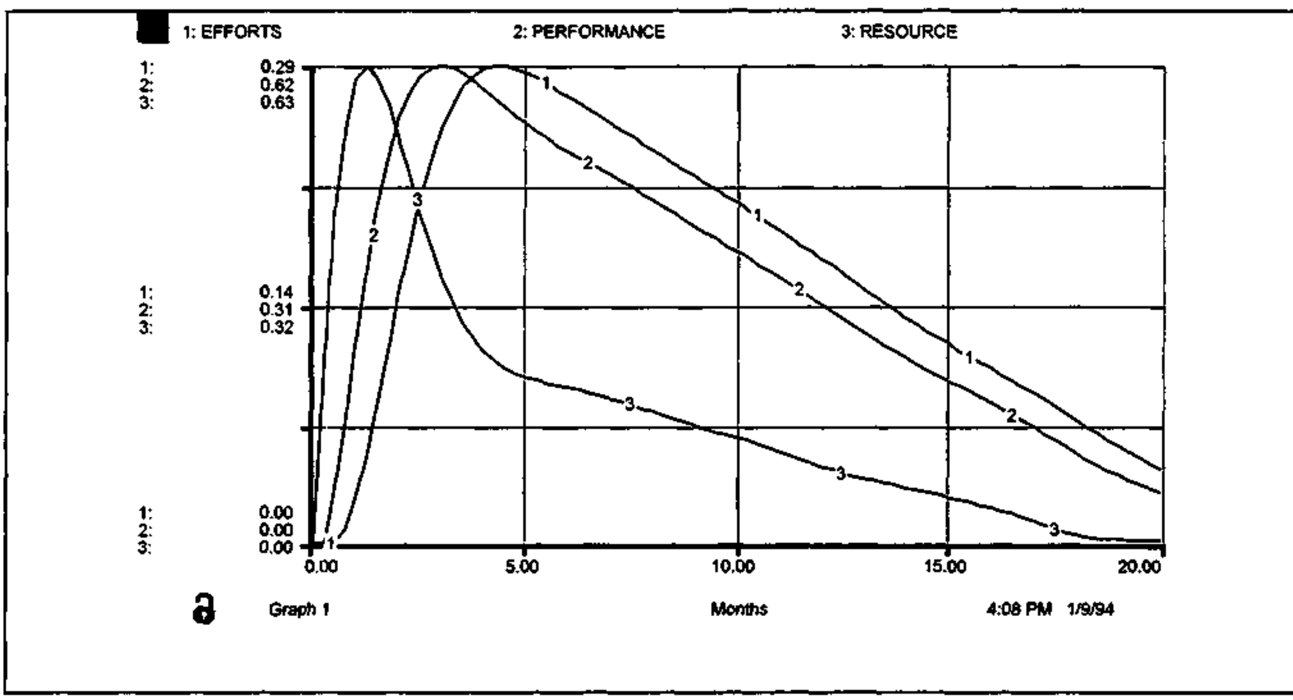
$$\text{Performance} = \text{Resource} + \frac{\text{Effort}}{2}$$

$$\text{Effort} = \text{Performance}$$

$$\text{Resource} = \text{Constraint} - \text{Performance}$$

Once some new balance has been established in this element in the model, the output begins to reflect reality, namely that no matter how hard you try, ultimately the availability of resources is the key to performance. The new equation reflects this in the following graph.

Fig 13: Graph for Limits to Success (ii)



This revised version is the result of two important processes. The first of these is local learning. The nature of the adjustments that are made at the local level, in this case the input to Performance, are the points at which the system can be made to function properly. While this is related to the Causal loop diagram idea of leverage, it is more than being the point at which greatest incremental change can be produced. It is the point which must be managed properly for the model to work at all.

The second is the identification of the point at which local learning takes place to best effect in this model. This balance is achieved in this model at the inflow to Performance. This is the balance between advertising dollars and inventory (the inflows to Performance) that needs to be learned to maintain the fundamental dynamics of the model. Various combinations can be tested to get the best outcome but the fundamental pattern must be that shown on Fig. 13 namely a decline in effort and performance in line with a declining resource. Put simply you can ease back on advertising as your stock declines.

A different decision may be to increase advertising in response to declining sales. This makes the point at which local learning must occur the input to Effort. Now any decline in Performance is translated into an increase in Effort.

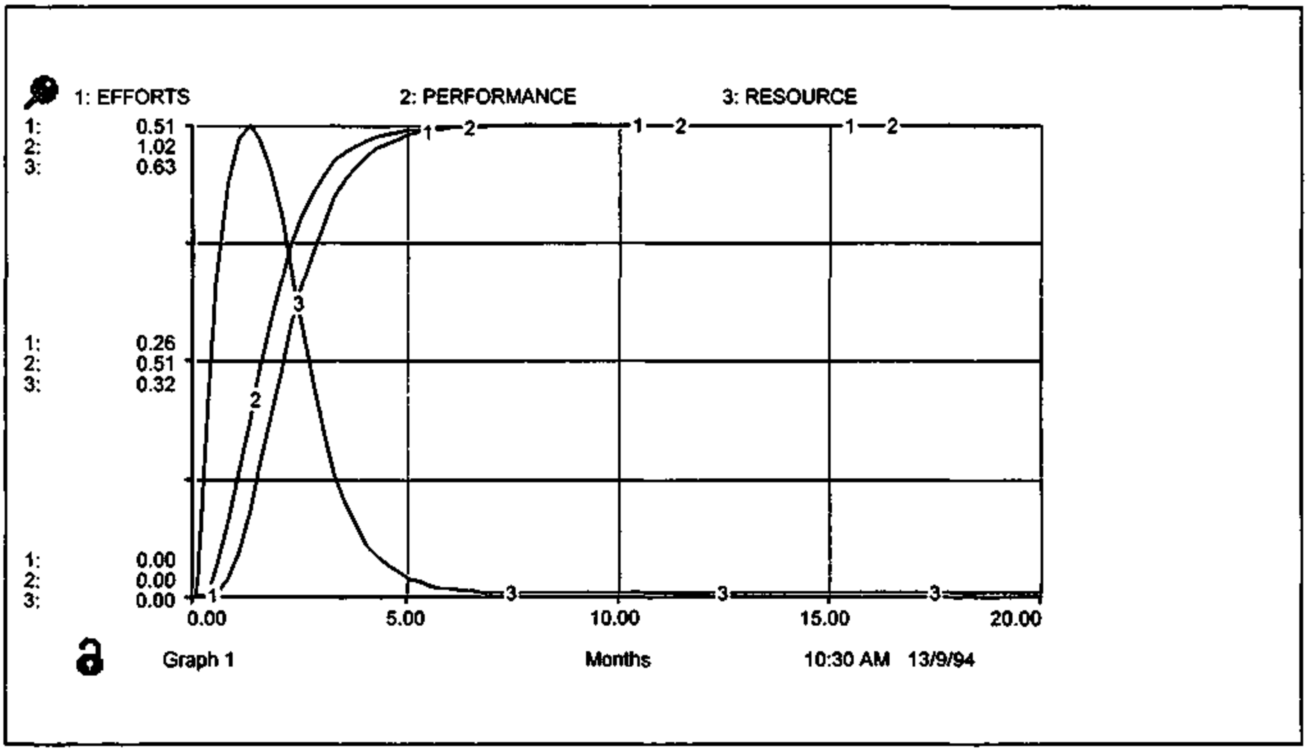
Performance = Resource + Efforts

Effort = Performance*2

Resource = Constraint - Performance

This leads to a return to the original "non-realistic" output. While the model says you can sell without stock, logic dictates that you cannot.

Fig 14: Graph for Limits to Success (i)

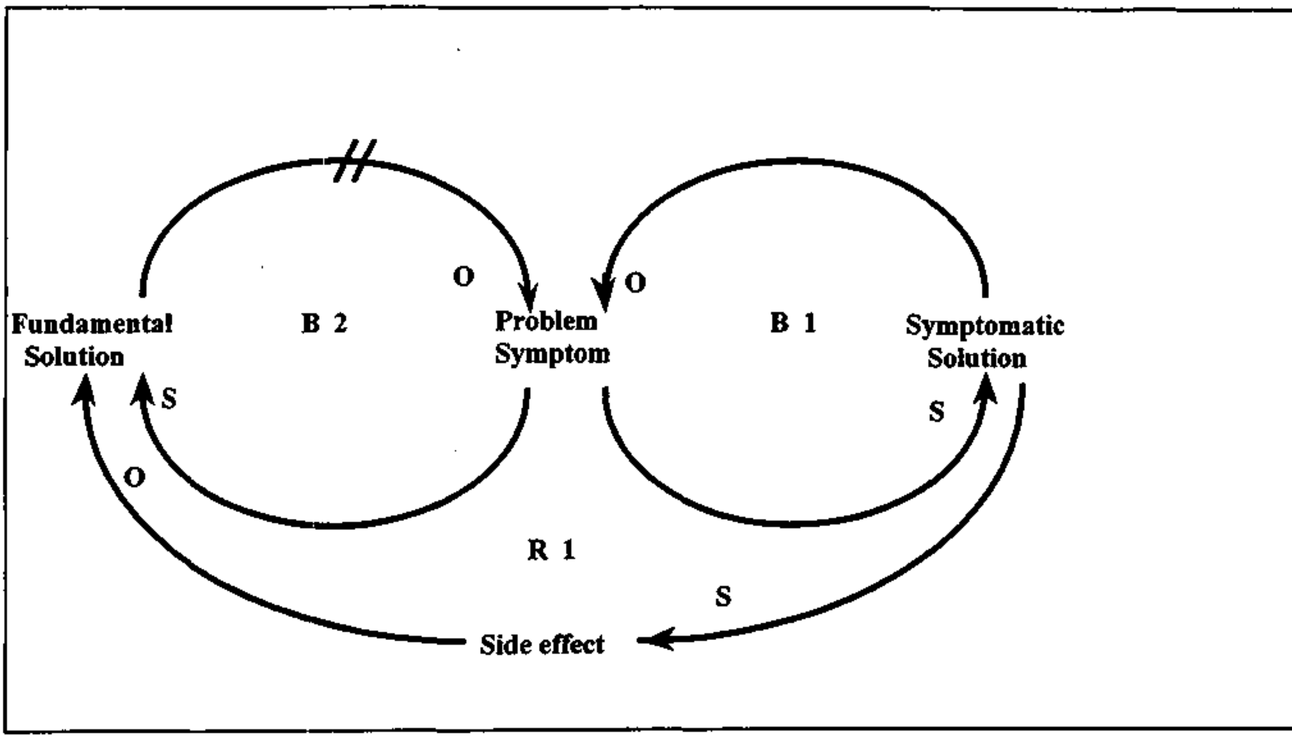


LOCAL LEARNING (ii): SHIFTING THE BURDEN.

The discussion of this model is designed to show how the local rules under which the stocks operate can affect the dynamics of the model. It also demonstrates that without the correct local learning in the model the output from the model is not what would be expected in reality.

To start with the archetype is explained by way of a short case study.

Fig 15: Causal Loop for Shifting the Burden



A highly innovative company that produces high tech machine components had gained its competitive advantage from its Research and Development team. With the launch of a radical new product it was faced with increasing levels of product failure in the field. It very quickly became clear that the sales support team, though skilled, was not going to be able to cope with the highly technical nature of these problems.

Concerned at the rising chorus of complaints from long standing customers, the CEO formed a group, later dubbed the Crisis Squad, of the best R + D people to deal with the problems. This proved to be successful for some time until one day he found a competitor was in the market place with a product that not only performed better but was also a significant technological advance on the product he had spent so much time and energy supporting.

It soon became obvious to the CEO that there had been a side effect of using the R+D staff in the band aid role of dealing with field complaints. This had been to decrease the amount of time R+D staff spent developing the quality in the product. In the long run that would have been the fundamental solution to the problem.

The archetype logic translates into the following iThink logic and model

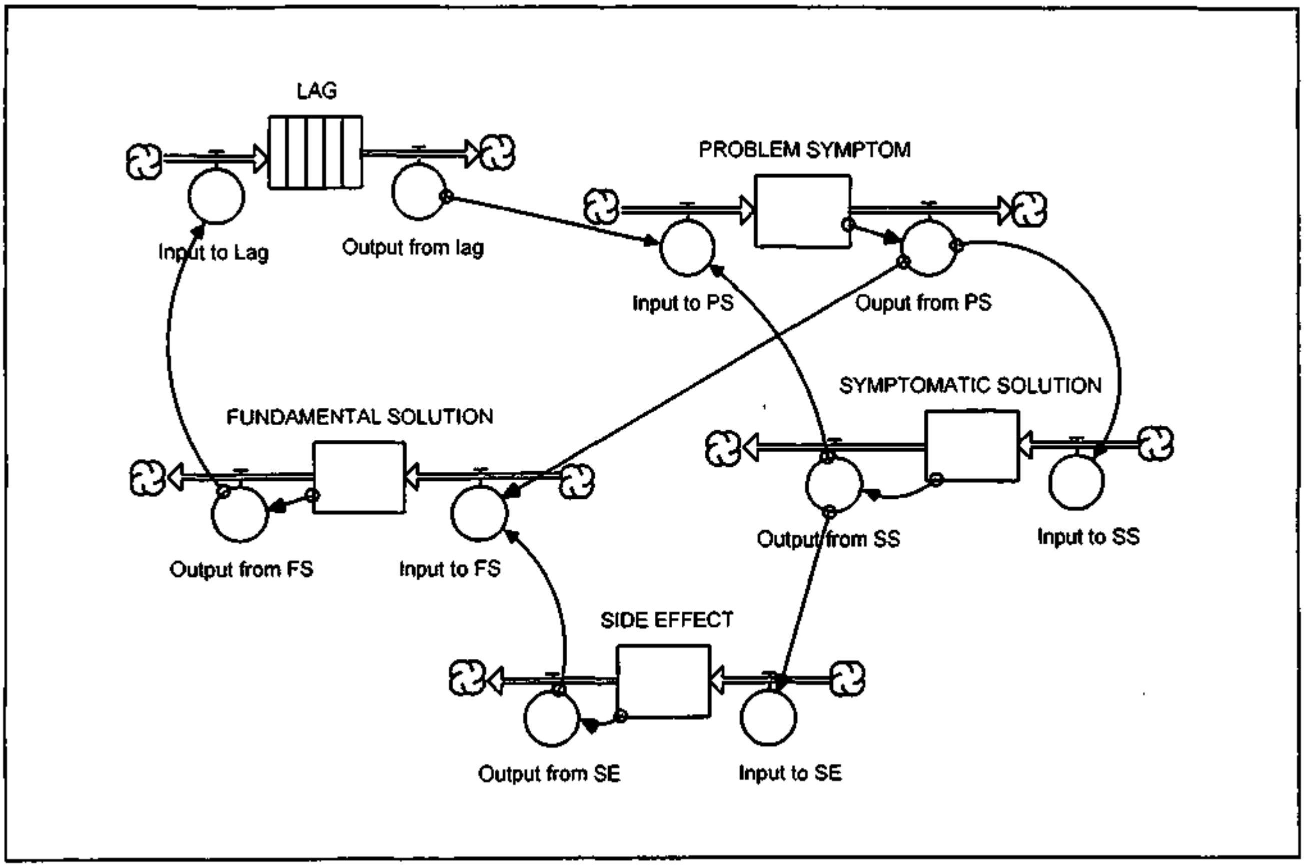
Problem Symptom = - Fundamental Solution - Symptomatic Solution

Symptomatic Solution = Problem Symptom

Fundamental Solution = Problem Symptom - Side Effect

Side Effect = Symptomatic Solution

Fig 16: iThink model for Shifting the Burden



The computer equations are as follows:

FUNDAMENTAL_SOLUTION(t) = FUNDAMENTAL_SOLUTION(t - dt)
+ (Input_to_FS - Output_from_FS) * dt
INIT FUNDAMENTAL_SOLUTION = 0
INFLOWS:
Input_to_FS = Ouput_from_PS-Output_from_SE
OUTFLOWS:
Output_from_FS = FUNDAMENTAL_SOLUTION

LAG(t) = LAG(t - dt) + (Input_to_Lag - Output_from_lag) * dt
INIT LAG = 0
INFLOWS:
Input_to_Lag = Output_from_FS
OUTFLOWS:
Output_from_lag = CONVEYOR OUTFLOW

PROBLEM_SYMPTOM(t) = PROBLEM_SYMPTOM(t - dt) + (Input_to_PS - Ouput_from_PS) *
dt
INIT PROBLEM_SYMPTOM = 1
INFLOWS:
Input_to_PS = (-Output_from_SS)-(Output_from_lag)
OUTFLOWS:
Ouput_from_PS = PROBLEM_SYMPTOM

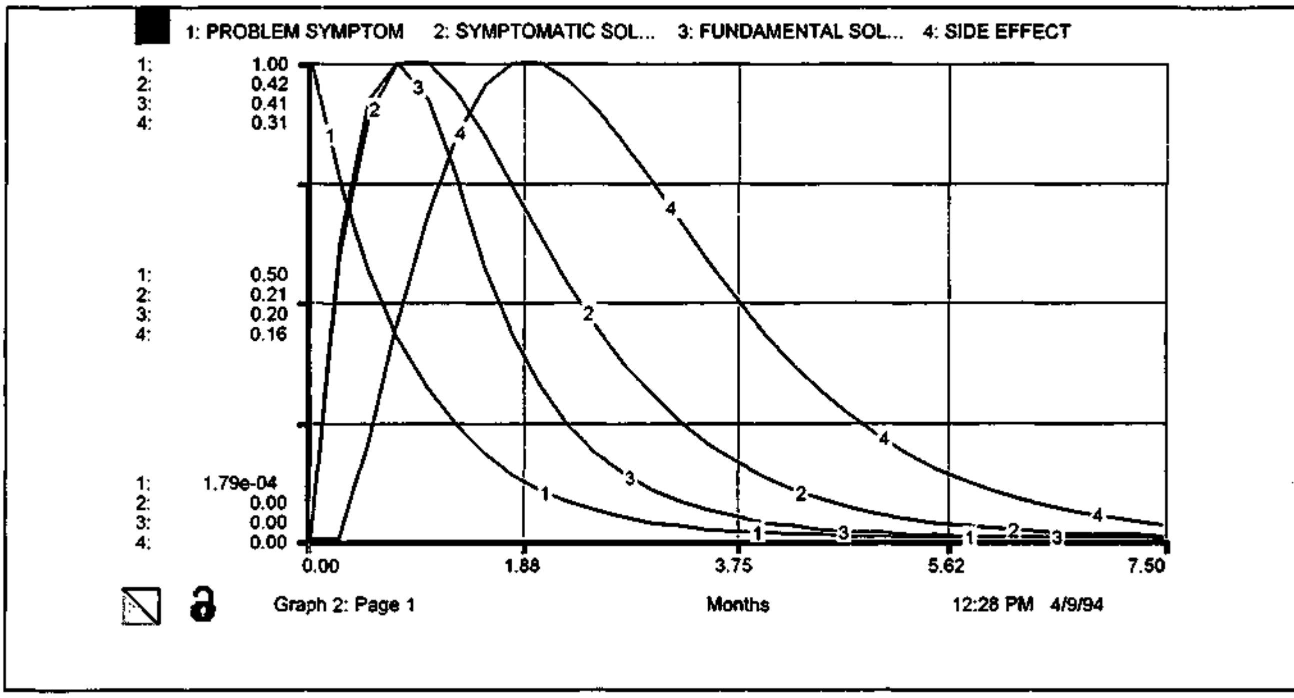
SIDE_EFFECT(t) = SIDE_EFFECT(t - dt) + (Input_to_SE - Output_from_SE) * dt
INIT SIDE_EFFECT = 0
INFLOWS:

Input_to_SE = Output_from_SS
OUTFLOWS:
Output_from_SE = SIDE_EFFECT

SYMPTOMATIC_SOLUTION(t) = SYMPTOMATIC_SOLUTION(t - dt)
+ (Input_to_SS - Output_from_SS) * dt
INIT SYMPTOMATIC_SOLUTION = 0
INFLOWS:
Input_to_SS = Ouput_from_PS
OUTFLOWS:
Output_from_SS = SYMPTOMATIC_SOLUTION

The action of the archetype is dominated by the balancing loop B1 in the Causal Loop.

Fig 17: Graph for Shifting the Burden (i)



Here the system has stabilized the Problem Symptom through the action of the balancing loop that includes the Symptomatic Solution. However, the fundamental premise of the Shifting the Burden or Addiction Archetype is that the use of the Symptomatic Solution leads to an increasing reliance on it. In addition the Symptomatic Solution suppresses the operation of the Fundamental Solution and worsens the problem. This simulation does not show this because of the automatic operation of Loop B2 which allows the Problem Symptom to trigger the Fundamental Solution. In fact, this ought not to be the case.

The Impact of Local Learning.

In the situation that is modelled below, we can examine the impact of local rules and local learning. In the situation of the customer complaints, one actor has decided that not all customer complaints will get attention.. However, this actor decides that certain types of complaints will not be dealt with or dealt with less quickly. In effect this actor learns "what you can get away with" Here the Symptomatic Solution is discounted or reduced by 1 The Symptomatic Solution is given a "slackness band aid factor" of

Problem Symptom = - (Symptomatic Solution -1)

or

Problem Symptom = (1 - Symptomatic Solution)

instead of the normal band aid tightness of

Problem Symptom = - Symptomatic Solution

Here the Problem Symptom was reduced in direct proportion to the Symptomatic Solution. The complete set of equations for this situations is:

Problem Symptom = (1-Symptomatic Solution) - Fundamental Solution

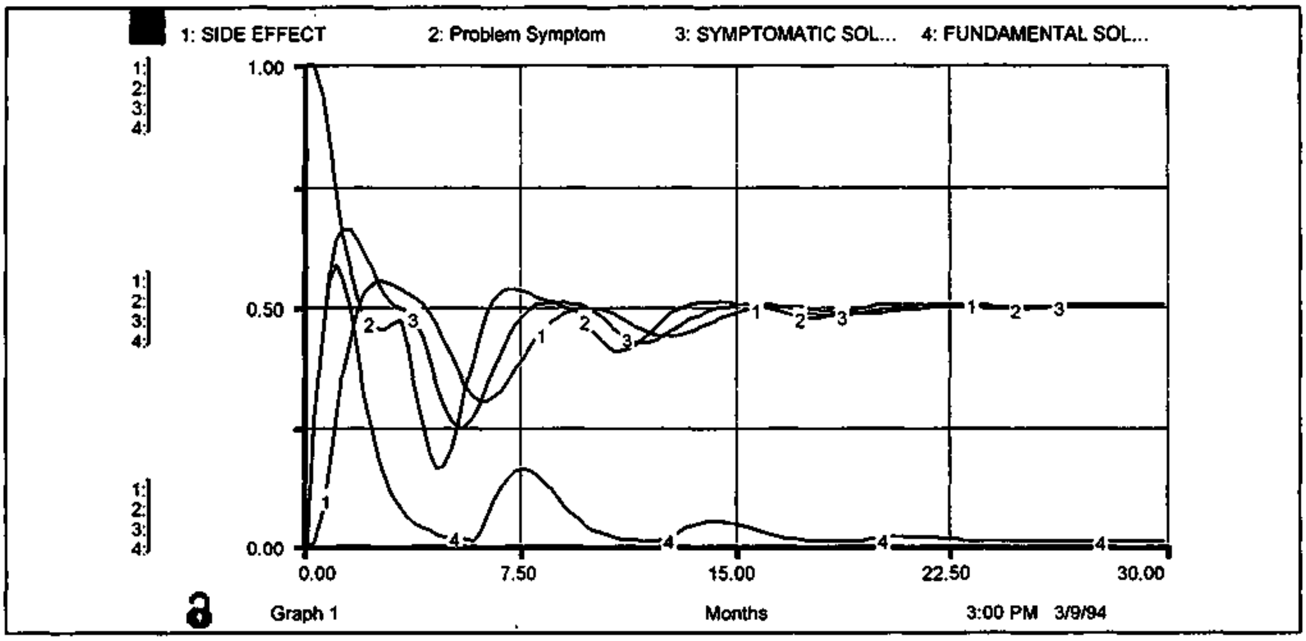
Symptomatic Solution = Problem Symptom

Fundamental Solution = Problem Symptom - Side Effect

Side Effect = Symptomatic Solution

The result of this Local Rule is an on-going level of complaints which are dealt with by the less than efficient band aid and the fundamental solution never really kicks in.

Fig 18: Graph for Shifting the Burden (ii)



The local learning here is that of the agent who decides on the level or type of response to customer complaints that is needed to stabilize his or her local environment. Because this agent is located in a balancing loop that rule serves to dissipate the fluctuations caused by the Problem Symptom and the system stabilizes in a new equilibrium.

A recent and practical example of local learning at this point in the archetype occurred in a large public utility. Frequent repairs needed to be done to a widely used item of equipment. Local rules developed about how well these repairs would be done so that there would always be a regular supply of weekend work at overtime rates.

The "Fix the Symptoms" Solution.

However, things are not like this in real life. As the symptoms of the problem, customer complaints about poor quality, get worse, someone somewhere will eventually do something of a more permanent nature. They will put in place what the archetype calls the "Fundamental Solution".

This action is included in the IF/THEN /ELSE logic equation set out below. Once customer complaints, reaches a certain crescendo of, say 10, some Fundamental Solution, in this case improving quality, must come into play. This is another example of local rules leading to local learning. Here the rule relates to the level of customer complaints that triggers a quality improvement response. As can be seen by the graph the systems stabilizes because in this case the local rule has not come into force. This si because the level of customer complaint is running below 10. This phenomenon is very common in organizations where certain levels of activity trigger either automatic systems, as in a smoke detector, or informal systems where someone decides to act in response to a certain level of activity, in simple terms closing a window when it feels too cold.

The equations for the model are as follows:

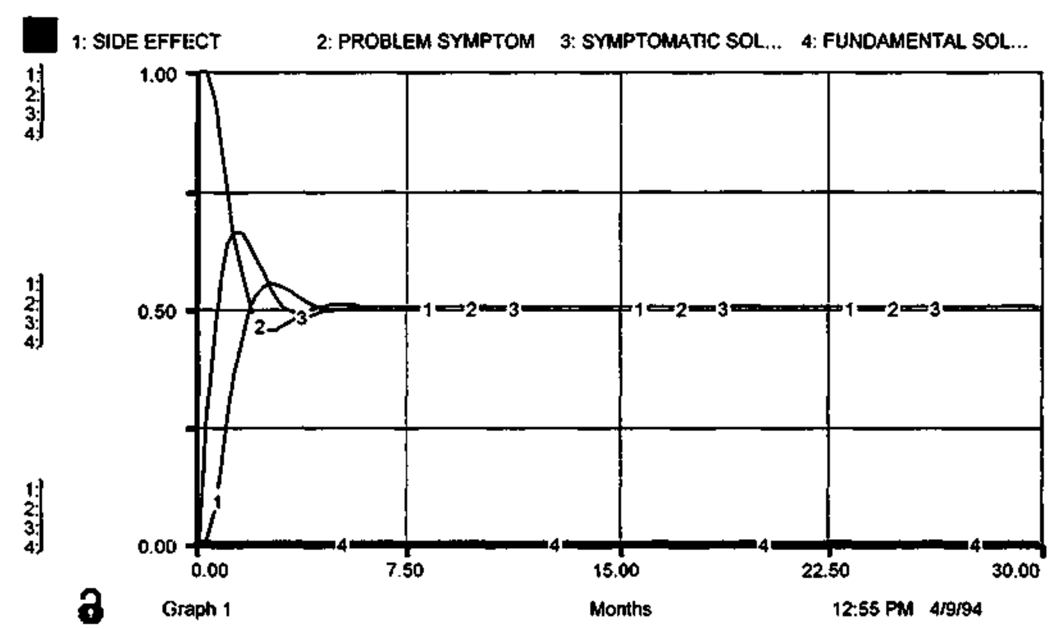
Problem Symptom = (1-Symptomatic Solution) - (Fundamental Solution)

Symptomatic Solution = Problem Symptom

Fundamental Solution = IF (Problem Symptom<10) THEN (- Side Effect) ELSE (Problem Symptom)

Side Effect = Symptomatic Solution

Fig 19: Graph for Shifting the Burden (iii)

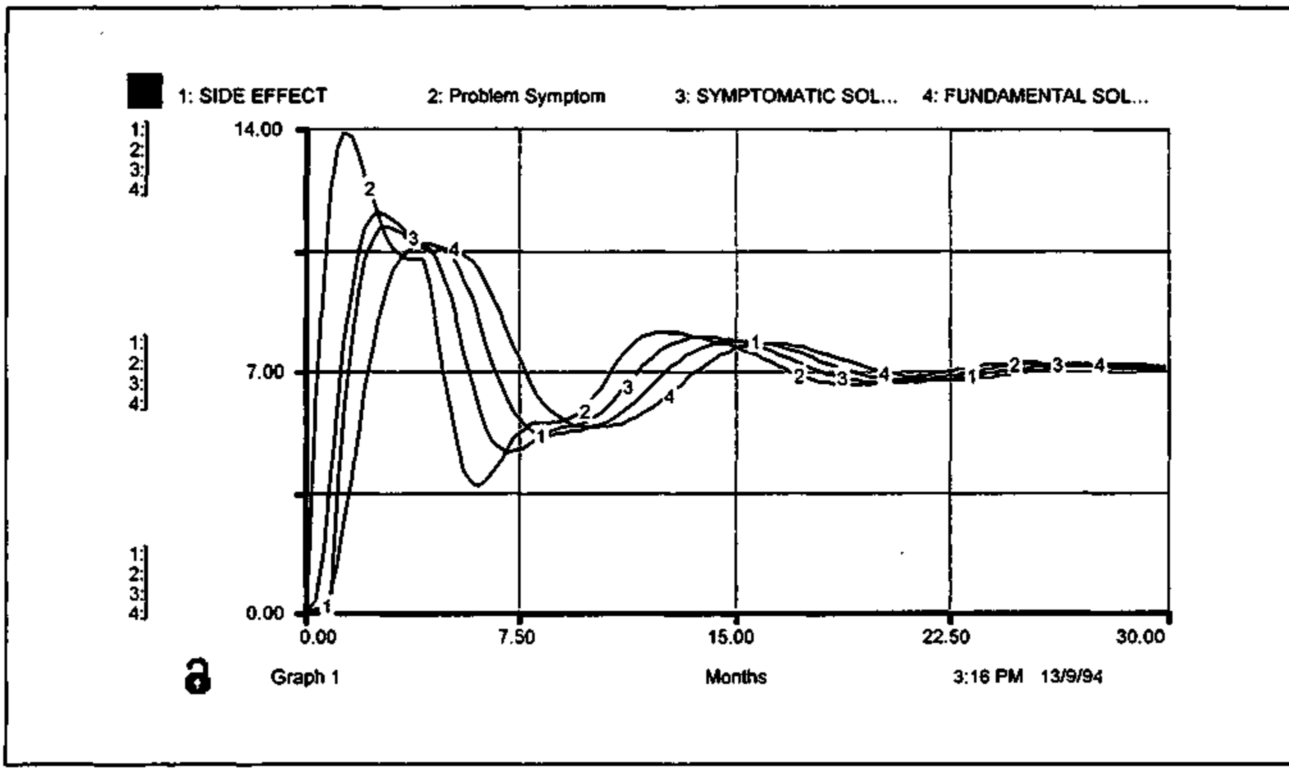


As the level of customer complaint is within the range that the local rules allow, there is no fundamental solution. The organization then tolerates a certain level of customer complaint.

A further example of this is the point at which a motor car manufacturer decides that they need a major recall of a model as distinct from an acceptable level of complaints about quality is an example of this. However, once the rate of complaints jumps above 10, the local rule that says this is unacceptable comes into operation. Notice that on the graph the local rule serves to drive complaints down but has not solved the problem.

In a wider context which is not to be developed in this paper, it is clear that some of the archetypes, and in particular, "Growth and Underinvestment" need IF/THEN/ELSE logic in them to ensure the switch into correcting loops once a certain system state is reached.

Fig 20: Graph for Shifting the Burden (iv)



Putting the Fundamental Solution in Place.

In this model the local rules are that there will be a Fundamental Solution to the complaints problem. The Symptomatic Solution will not be allowed to impede the functioning of this section of the system. Thus while there may be a Symptomatic Solution in operation it is not allowed to "De-sensitise" the Fundamental Solution from the messages from the Problem Symptom.

When the Problem Symptom is able to trigger the Fundamental Solution the impact of the Side Effect is diminished. In the real world, the local rules could be that every customer complaint must be met with a "no faults" replacement product made at the expense of the department responsible for the failure (this diverts the customer complaint a the Fundamental Solution loop) and that the Head of Research refuses to let research staff do site visits (this reduces the impact of the Side Effect to 1-Side Effect.).

Fundamental Solution = Problem Symptom + (1- Side Effect)

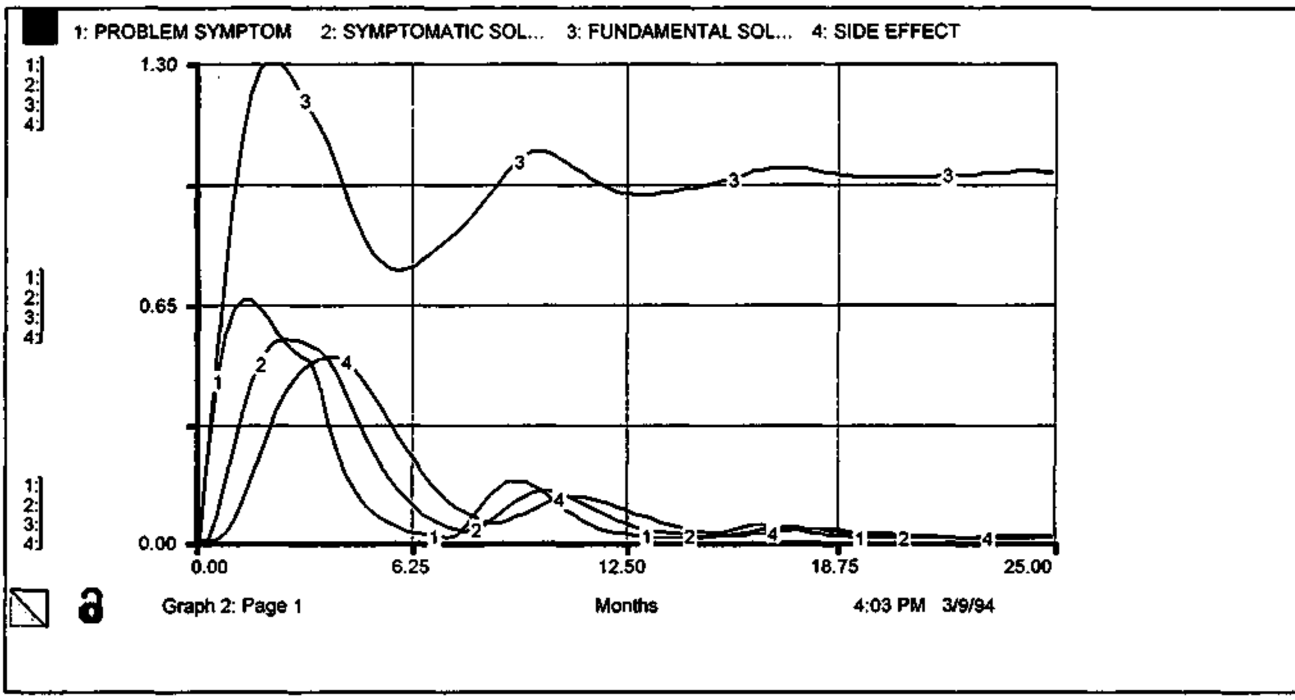
Problem Symptom = (1 - Symptomatic Solution) - Fundamental Solution

Symptomatic Solution = Problem Symptom

Side Effect = Symptomatic Solution

Fig 21 shows these two local rules have worked in concert to re-establish a highly desirable equilibrium where customer complaints are declining. It is interesting to note that the decision of the Head of Research has had the result of lowering customer complaints simply because the Research staff are no longer available to do site visits. This is a logical and reasonable outcome once the dynamics of the system are understood but in complex systems it is often difficult to be instinctively aware of the outcome of policy decisions. It is the great strength of simulations that the impact and interaction of policy can be examined.

Fig 21: Graph for Shifting the Burden (v)



The operation of the Shifting the Burden Archetype is far more complex that the causal loop would suggest. The first reason for this is that the impact of the Problem Symptom in triggering the Fundamental Solution is not explicit in the Causal Loop. For a company to break the pattern of Symptomatic Solutions inhibiting the use of Fundamental Solutions, Loop B2 must predominate over R1.

The second reason for the increased complexity of the computer model is the impact of local learning where actors at different points in the system impose local rule to stabilize their immediate environment. Variation in these rules produces very different dynamics within the system.

CONCLUSION

While the Senge archetypes shed light on processes within organizations and provide a useful introduction to Systems Thinking, the intellectual technology of Causal Loop Diagramming is ultimately too simplistic for the serious systems thinker. There are complexities in systems that the Causal Loop Diagramming does not expose. Primarily these complexities relate firstly to the phenomenon of local learning which is embedded in the operations of the system and secondly to the dynamics of local learning, in particular in terms of dissipation of perturbation. These systemic interactions cannot be demonstrated or indeed understood without the use of computer simulations of systems models. While the Senge archetypes have been used for the purpose of this discussion, the principles relating to the level of analysis are true of all modelling. Computer model building provides both researcher and practitioner with a means for a deeper and more complex understanding of systems theory.

REFERENCE

Senge, P. The Fifth Discipline Viking, 1992.