A Comprehensive Model of Goal Dynamics in Organizations: Setting, Evaluation and Revision[1,2]

Yaman Barlas
Bogazici University, Dept. of Industrial Eng.
34342 Bebek, Istanbul – Turkey
Tel: +90 212 359 7073, Fax: +90 212 265 18 00
ybarlas@boun.edu.tr

Hakan Yasarcan
Accelerated Learning Laboratory
Australian School of Business (Incorporating the AGSM)
The University of New South Wales
Sydney, NSW 2052 – Australia
Tel: +61 2 9931 9193, Fax: +61 2 9931 9517
hakany@agsm.edu.au

Goal setting plays a central role in most simulation models of individual or social behavior. In the simplest case, there is a constant goal and the modeling effort focuses on the difficulties involved in reaching that given goal. In more realistic situations, the goal itself is variable: it can erode as a result of various phenomena such as deeply rooted traditions or frustration due to persistent failure, it can evolve further as a result of confidence caused by consistent success, or it can be consciously evaluated and adjusted periodically as a result of some formal process. In any case, 'goal dynamics' constitutes a fundamental sub-problem in most situations dealing with dynamics of individual or social behavior. As such, there has been considerable research effort on how to model the dynamics of goal formation in system dynamics models. With respect to the three types of goal dynamics mentioned above, in the literature there exist some model structures that capture certain limited and linear 'goal erosion' dynamics. We extend the existing models to obtain a most general theory of goal formation dynamics, by including performance improvement capacity constraints, short term and long term time pressures in reaching the set goal and more realistic, richer mechanisms of goal erosion. We show that the system can exhibit very subtle non-linear problematic dynamics in such cases. The model is generic in the sense that it offers a general theory of goal formation, including potential goal erosion (caused by persistent poor performance) as well as positive goal evolution dynamics (as a result of consistent success), and more complex dynamics resulting from interactions of these two extremes. Our model also offers some adaptive goal setting strategies to avoid the undesirable goal and performance erosion dynamics typically experienced in complex, risky goal-seeking environments.

Keywords: goal seeking, goal dynamics, goal formation, goal revision, floating goals, goal erosion, goal evolution, goal setting strategy

[1] *Supported in part by Bogazici University Research Funds; grants no: 02R102 and 06HA305*
[2] *To appear in: Qudrat-Ullah, H., Spector, M., and Davidson, I. (Eds.). Complex Decision Making: Theory and Practice, USA: Springer-Verlag, to be in print in 2007. (Reprinted for this conference with permission).*

INTRODUCTION

Goal setting plays crucial role in decision making in organizations as well as in individuals. Most improvement activities consist of the following cycle: set a goal, measure and evaluate the current performance (against the set goal), take actions (e.g. training) to improve performance, evaluate and revise the goal itself if necessary, again measure and evaluate the performance against the current goal, and so on … [Forrester 1975; Senge 1990; Lant 1992; Sterman 2000]. So goals constitute a base for the decisions and the managerial actions. In an organization, the performance level is evaluated against a goal and, further, the effectiveness of the goal itself can and must be periodically evaluated.

Among various research methods to analyze the dynamics of goals in organizations (and individuals), an important one is simulation modeling – more specifically *system dynamics* modeling that is particularly suitable to model qualitative, intangible and 'soft' variables involved in human and social systems [Forrester 1961; Forrester 1994; Morecroft and Sterman 1994; Sterman 2000; Spector et al 2001]. *System dynamics* is designed specifically to model, analyze and improve dynamic socio-economic and managerial systems, using a feedback perspective. Dynamic strategic management problems are modeled using mathematical equations and computer software and dynamic behavior of model variables are obtained by using computer simulation [Forrester 1961; Ford 1999; Sterman 2000; Barlas 2002]. The span of applications of the system dynamics field includes: *corporate planning and policy design, public management and policy, micro and macro economic dynamics, educational problems, biological and medical modeling, energy and the environment*, and more [Forrester 1961; Roberts 1981; Senge 1990; Morecroft & Sterman 1994; Ford 1999; Sterman 2000]. Since these problems are typically managerial-policy oriented, structures that deal with goal dynamics play an important role in most system dynamics models. It is therefore no surprise that modeling of goal dynamics is an explicit research topic in system dynamics.

A fundamental notion and building block used in most policy models, is a 'goal seeking' structure that represents how a certain condition (or state) is managed so as to reach a given 'goal' (see Figure 1 and 2 below). For instance, the state may be the inventory level or delay in customer service, and the goals would be a set (optimal) inventory level or a targeted service delay respectively. [For numerous examples see Sterman 2000 and Forrester 1961]. Management would then take the necessary actions (*Improvement* in Figure 1) so as to bring the states in question, closer to their set goal levels. The most typical heuristic used to formulate *Improvement* is:

$$Improvement = (Goal - State)/SAT$$

where *SAT*, *State adjustment time*, is some time constant. The dynamics of this simplest goal seeking structure is depicted in Figure 2: *State* approaches and reaches the *Goal* gradually, in a negative exponential fashion. In more sophisticated and realistic goal-seeking models, the goal is not fixed; it varies up and down depending on current conditions, called a 'floating goal' structure [Sterman 2000; Senge 1990]. In this case, if the performance of the system is persistently poor (in approaching the originally set goal), then the system implicitly or deliberately lowers the goal (*eroding* goal). If, on the other hand, the system exhibits a surprisingly good performance, then the goal may be pushed further up (*evolving goal*). Another key component of a general goal setting structure is *expectation formation*: Goals are set and then adjusted in part as a function of future expectations [Forrester 1961; Sterman 1987]. This may involve the expectations of management, expectations of participants, or typically both. Formulation of expectations is a rich research and modeling topic with its roots in theories of cognitive research in policy making [Spector and Davidsen 2000] and rationality; ranging from rational expectations to *satisficing* and bounded rationality [Simon 1957; Morecroft 1983]. So, formulation of goal setting, evaluation and seeking is a deep and important research topic in system dynamics modeling.

In this paper we present a comprehensive goal dynamics model involving different types of explicitly stated and implicit goals, expectation formation and potential goal erosion as well as positive goal evolution dynamics. We further include a host of factors not considered before, such as organizational capacity limits on performance improvement rate, performance decay when there is no effort, time constraints, pressures and, motivation and frustration effects. We show that the system can exhibit a variety of subtle problematic dynamics in such a structure. The modeling setting assumed in the paper is an organization in which a new 'performance' goal is set and a new program (e.g., a training activity) is started to achieve the goal. In a service company, this may be a new training program set 'to increase the customer satisfaction from 60% to 80% in one year' as measured by customer surveys. Or in a public project, this may be a new educational program in a poor neighborhood set 'to increase the functional literacy rate from 80% to 90% in three years' as measured by periodic tests. So there is a goal and there is also a time horizon set to reach the goal. Note also that the environment described above implies that the *Goal* is always approached from below and higher *State* levels mean always better for the system. (As opposed to inventory management, where there is some 'optimal' target inventory level so that the management increases the inventory if it is too low compared to the set goal and lowers the inventory if it is too high).

The paper starts by elaborating on the simplest model of constant goal seeking dynamics, by including a *constraint* on improvement *capacity* and a nominal *decay* rate out of the state variable (Figure 3). We then gradually add a series of more realistic and complex goal-related structures to the initial model. The purpose of each addition is to introduce and discuss a new aspect of goal dynamics in increasingly realistic settings. In the first enhancement, we introduce how the implicit goal in an organization may unconsciously erode as result of strong past performance traditions. Next, we discuss under what conditions recovery is possible after an initial phase of goal erosion. In the following enhancement, we include the effects of *time constraints* on performance and goal dynamics. Many improvement programs have explicitly stated time horizons and the pressure (frustration) caused by an approaching time limit may be critical in the performance of the program. We also show that in such an environment, the implicit *short-term* self-evaluation horizons of the participants may be very critical in determining the success of the improvement program. Finally we propose and test an adaptive goal management policy designed to assure satisfactory goal achievement, by taking into consideration the potential sources of failures discovered in the preceding simulation experiments. We conclude with some observations on implementation issues and further research suggestions.

THE SIMPLE GOAL SEEKING STRUCTURE AND ITS DYNAMIC BEHAVIOR

The simplest goal-seeking structure consists of a single fixed goal, a condition (called *State* in Figure 1) that is managed and a management action (*Improvement* in Figure 1). Once the goal is set, it is not challenged by the internal dynamics of the system or by any external factor. As mentioned before, assuming a typical stock adjustment heuristic (i.e. *Improvement* = (*Goal* – *State*)/*SAT*), this structure exhibits a pure negative exponential goal-seeking behavior shown in Figure 2.

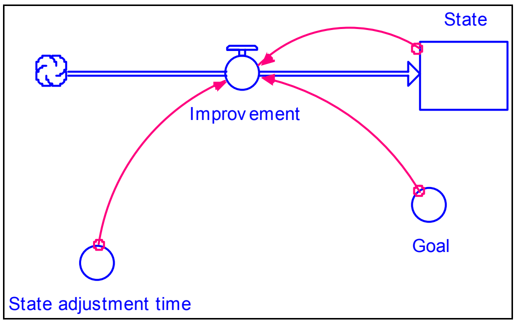

Figure 1. The simplest goal seeking structure (stock-flow diagram)

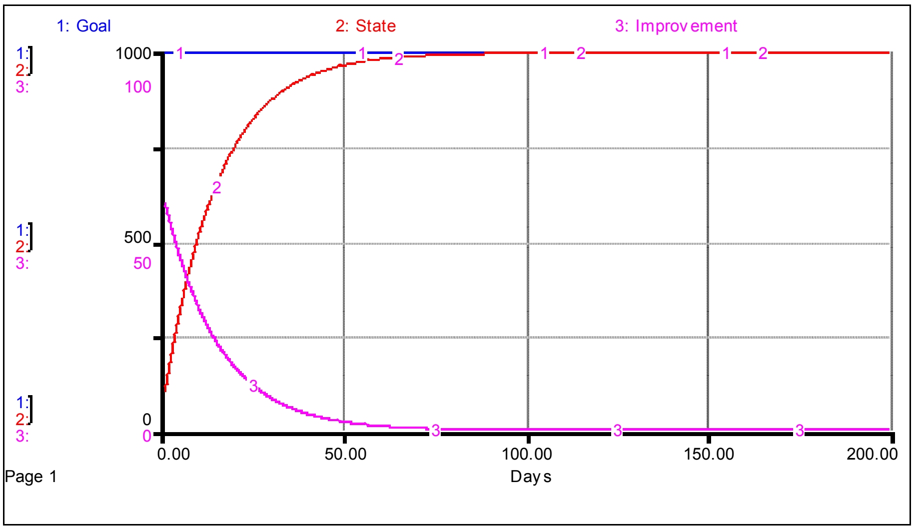

Figure 2. The simple goal seeking behavior generated by the model of Figure 1

In our enhanced version of this simplest goal-seeking structure, we introduce two new factors to make it more general and realistic:

- i- If there is no improvement effort, *State* experiences a natural decay (*Loss* flow) and,
- ii- *Improvement* rate is (naturally) limited by some *Maximum capacity*.

The outflow, *Loss* is assumed to be simply a fraction (*loss fraction*) of the actual *State*. This implies in essence that due to rapidly changing hi-tech organizational setting, the performance level tends to decay over time, if no improvement effort is undertaken. Proportional formulation means that as *State* goes up, so does the *Loss* rate. This is realistic to some extent, but to prevent exaggeratedly high *Loss* rates, we place a limit on *Loss* as well, called *Maximum loss*. (We choose *Maximum loss* to be less than *Improvement capacity*, otherwise it would be impossible to ever fulfill the *goal*).

Maximum capacity is constant in our models, as capacity management is beyond the scope of this paper. The effective *Improvement capacity*, on the other hand is variable ($Accomplishment\_motivation\_effect \times Maximum\_capacity$), but in this first model *Accomplishment motivation effect* is equal to one, so it has no role yet. (It will have an important role later in the enhanced versions of the model). In any case, *Improvement* is thus formulated as:

$$Improvement = MIN(Desired\_improvement, Improvement\_capacity)$$

The *Desired improvement* formulation is the standard 'anchor-and-adjust' formulation [Sterman 1989; Sterman 2000; Barlas and Ozevin 2001; Yasarcan 2003]. It is given by:

$$Desired\_improvement = Estimated\_loss + State\_adjustment$$

$$State\_adjustment = (Stated\_goal - State)/State\_adjustment\_time$$

So the *Desired improvement* decision uses *Estimated loss* as an anchor and then adjusts the decision around it, depending on the discrepancy between the goal and the current state. Since it is not possible to know the *Loss* immediately and exactly, it must first be estimated by the decision maker or system participants. So, *Estimated loss* is the output stock (see Figure 3) of an expectation formation structure, using simple exponential smoothing formulation:

$$Estimation\_formation = (Loss - Estimated\_loss)/Estimation\_formation\_time$$

Estimation formation time represents the delay in learning the actual value of performance *Loss*. All stock, flow and converter variables are shown in Figure 3.

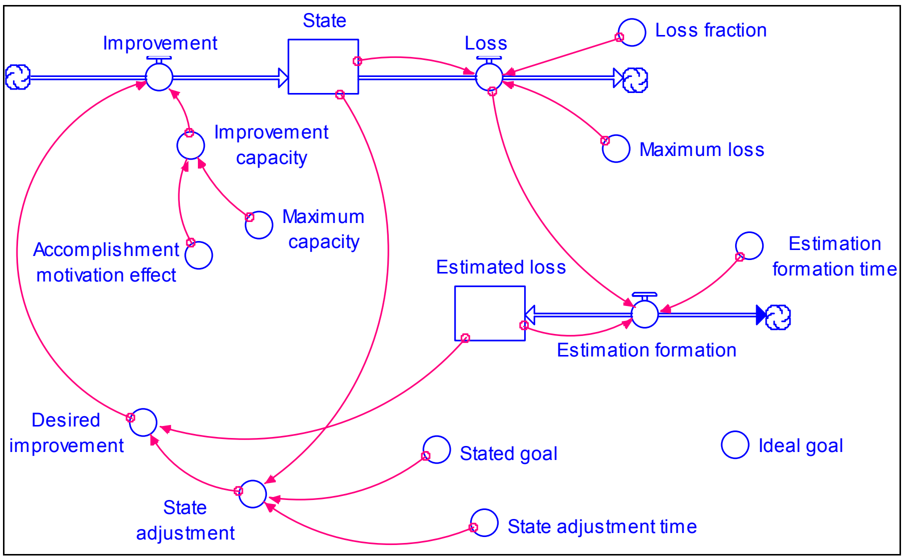

Figure 3. Simple goal seeking model with improvement capacity limit and loss flow

Note that there are two different goal variables in Figure 3; *Stated goal* is set and declared by the management, and *Ideal goal* is defined as the best (highest) possible goal for the system. In this first simple model, *Stated goal* is assumed to be equal to the *Ideal goal.* (In all simulation experiments, initial *State* is taken as 100 and *Ideal goal* as 1000. In the simpler models and experiments, *Stated performance goal* is equal to *Ideal goal*, but especially in more complex models, *Stated goal* will not be necessarily equal to the *Ideal goal*, and in the final model it will not even be constant).

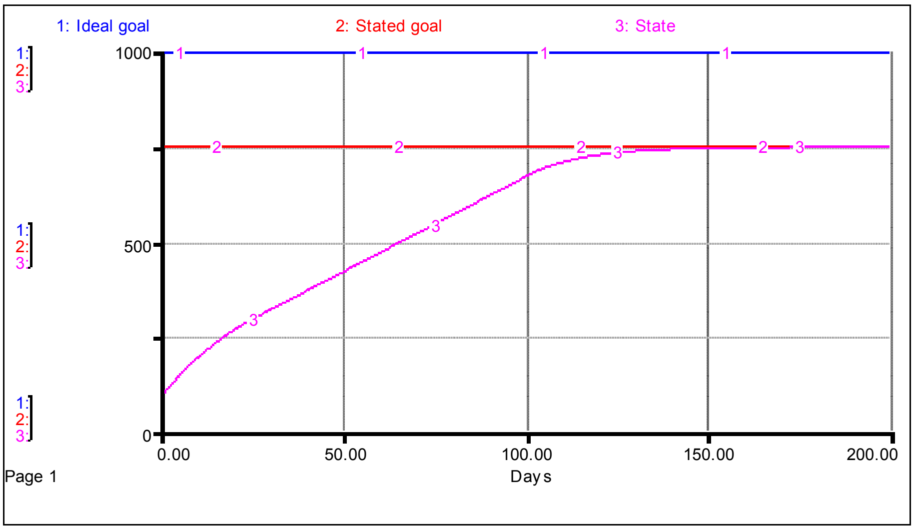

Figure 4. Goal seeking behavior generated by the model of Figure 3 (*Stated_goal* = 750)

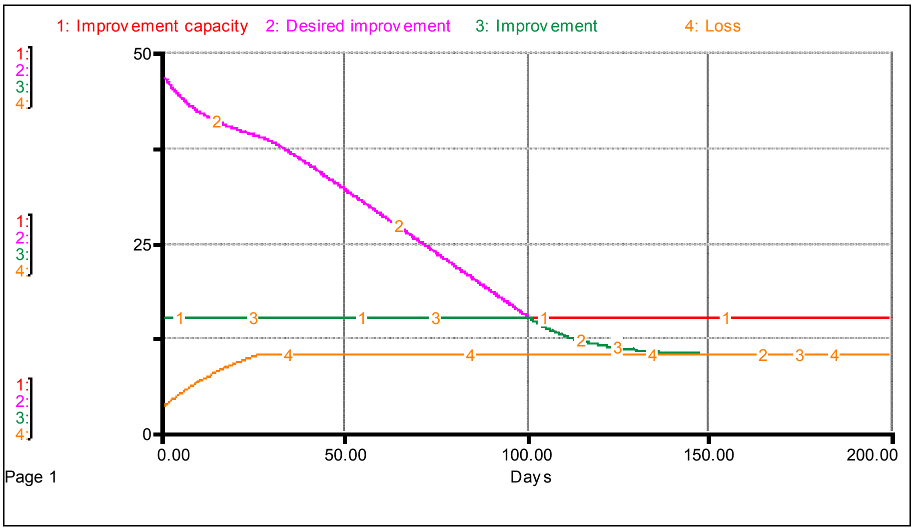

Figure 5. Dynamics of flows related to the run in Figure 4

Dynamic behavior generated by simulating the model of Figure 3 can be seen in Figures 4 and 5. The behavior is a variant of standard 'goal-seeking behavior' seen in Figure 2. *State* (line 3 in Figure 4) gradually seeks the *Stated goal*. Since the *Improvement* rate (line 3 in Figure 5) is above the *Loss* rate (line 4 in Figure 5), the *State* level keeps increasing until it reaches the *Stated goal*, at which point the improvement is lowered down to the *Loss* rate, since the goal is reached. Also observe (in Figure 5) that when the *Desired improvement* (line 2) is above the maximum improvement capacity (line 1), the actual improvement rate stays constant at *Maximum capacity*. When *Desired improvement* is below the *Maximum capacity*, then the actual improvement becomes equal to the *Desired improvement*.

This model is still too simple, being basically of introductory pedagogical value. The model can explain simple goal seeking dynamics like heating of a room or a water tank filling up to a desired level after flushing. In order to represent goal dynamics of human systems and organizations, we incorporate a series of realistic enhancements in the following sections.

TRADITIONAL PERFORMANCE, IMPLICIT GOAL AND EROSION

Goal erosion may occur if there is an endogenously created, undeclared, *Implicit goal* that system seeks, instead of the explicitly set goal (*Stated goal*). The model shown in Figure 6, is more realistic and complex version of the simple goal seeking model, involving the structures related to *Implicit goal* and eroding goal dynamics. Observe two important new variables in Figure 6: *Traditional performance* and *Implicit goal*. *Traditional performance* [Forrester 1975] represents an implicit, unconscious habit formation in the system. The human element in the system gradually forms a belief (a self image) about his/her own performance as time passes, and this learned performance (*Traditional performance*) may start to have even more effect than the *Stated goal* [Forrester 1975; Senge 1990; Sterman 2000]. The accumulation of the individual beliefs creates a belief within the system that the system can realistically perform around this past performance. To represent this mechanism, we assume that the system creates its own internal goal called *Implicit goal*, and seeks this new goal instead of the managerially *Stated goal*.

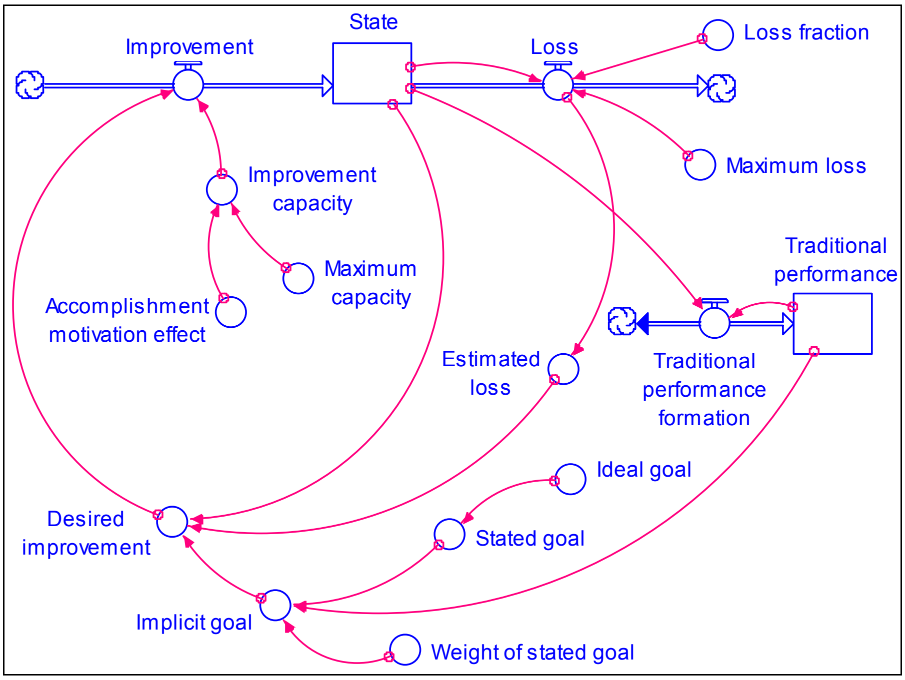

Figure 6. A basic model of eroding goal dynamics

Observe that in the model of Figure 6, there are only two new variables compared to Figure 3. The first one is *Traditional performance* which is essentially a historical (moving) average of past performance (*State*). This is formulated by simple exponential smoothing (with a tradition formation time of 30 days), just as it was done to formulate *Estimated loss*, above. The second one is *Implicit goal*, which is assumed to gradually tend to the *Traditional performance*, starting with an initial value of *Stated goal*. (There is a new parameter in Figure 6 called *Weight of stated goal* that should be ignored at this point, as it has no role in this version of the model; this parameter will have a role in the following section). So in a nutshell, *Implicit goal* is also an exponentially delayed function of *traditional performance:*

$$Implicit\_goal = SMTH3(Traditional\_performance, 10, Stated\_goal)$$

The third-order exponential smoothing function (SMTH3) used above means that the output (*Implicit goal)* does not immediately react to a change in the input (*Traditional performance);* there is a period of initial inertia. *Implicit goal* does erode to *Traditional performance*, but the erosion should not start immediately and should not react to any temporary change in traditional performance. Finally, the goal used in the *Desired improvement* equation is now *Implicit goal* (instead of *Stated goal*).

We assume that in a new improvement program, in the beginning there is no concept of past performance, so the human participants in the system completely accept the *Stated goal* as their goal (i.e. *Implicit_goal = Stated_goal)*. But as time passes, *Traditional performance* starts to have bigger effect and the *Implicit goal* starts approaching the *Traditional performance* instead of staying at the managerially *Stated goal*, a phenomenon often called *'goal erosion*'. Note that together with this goal erosion, the *State* starts to pursue the *Implicit goal*, not the *Stated goal*, so the result of the improvement program is a failure. The dynamic behaviors of goal erosion can be seen in Figure 7.

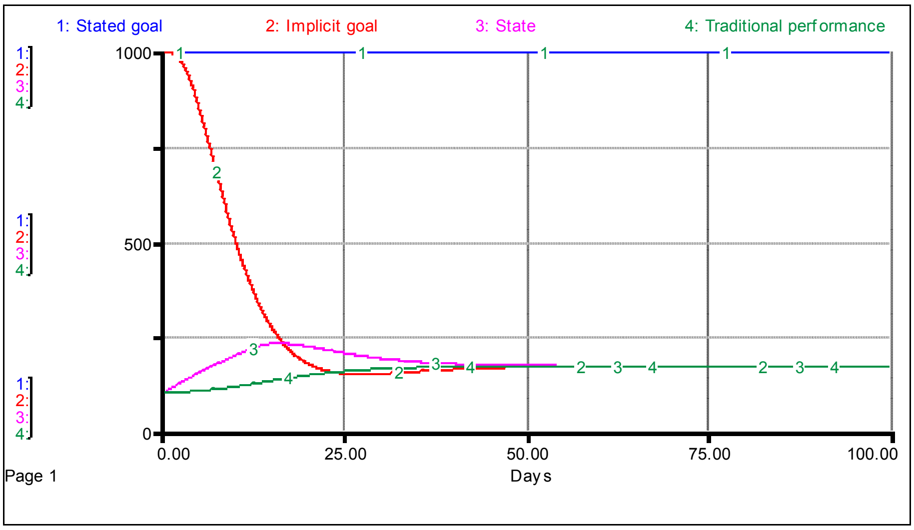

Figure 7. Strong erosion in goal, caused by *Traditional performance* bias

Goal erosion can be severe or mild, depending on some environmental factors. In the scenario represented in Figure 7, we assume that the *Traditional performance formation time* is relatively long (there is a strong past tradition), so the *Implicit goal* erodes toward *Traditional performance* and may erode to the point of even crossing below the current *State* level, since the highly delayed *Traditional performance* determines the *Implicit* *performance goal* (see Figure 7). Erosion can be extreme if there is a very strong past tradition. Conversely, if the tradition formation time is short, then goal erosion is milder and also simpler: since with a short formation time, *Traditional performance* is almost equal to current *State*, the *Implicit goal* would be effectively seeking the *State* (and the *State* naturally seeking the *Implicit goal*).

GOAL EROSION AND RECOVERY

In the model shown in Figure 6, if the parameter *Weight of stated goal* is given a value between 0 and 1, then the equation of *Implicit goal* becomes:

$$Implicit\_goal = SMTH3[Weight\_of\_stated\_goal \times \mathrm{Stated\_goal} + (1\text{-}Weight\_of\_stated\_goal) \times Traditional\_performance,\ 10]$$

The above equation states that *Implicit goal* is now basically a weighted average of the S*tated goal* and *Traditional performance*. This weighted average is then passed through a third-order smoothing to give it a realistic inertia, just as in the previous model. (But in the previous version, *Weight of stated goal* was set to 0, so that *Implicit goal* was simply exponentially eroding to *Traditional performance*, starting with an initial S*tated goal*). In the current version of the model, participants are affected both by the external S*tated goal* and by their *Traditional performance,* so that their *Implicit goal* is somewhere in between the two extremes [Forrester 1961; Sterman 2000; Barlas and Yasarcan 2006]. *Weight of stated goal* determines how much the system believes in *Stated goal.*

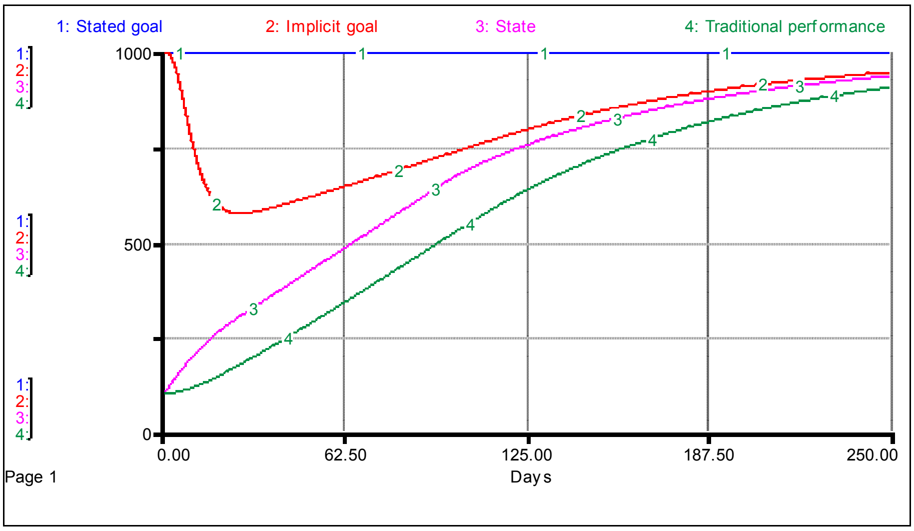

Figure 8. Behavior of goal erosion and recovery model (*Weight_of_stated_goal* = 0.5)

The resulting dynamics with *Weight_of_stated_goal* = 0.5 are shown in Figure 8. After a significant initial erosion, *Implicit goal* and hence *State* gradually recover towards S*tated goal.* Observe that since *Traditional performance* is an exponential average of past *State* values, the former moves - fast or slow- towards the *State* after some delay. On the other hand, the other component of the weighted average, S*tated goal* is fixed. The net result is that all variables, including *Traditional performance* eventually recover and gradually approach S*tated goal* over time (Figure 8). Thus, although this model is more realistic than the previous version in some sense, it suffers from the following fundamental weakness: the formulation implies that, even though a system may suffer from initial goal and performance erosion, in time it will always recover (fast or slow) and attain the S*tated goal*. The weakness is that there is no notion of 'time horizon' and potential frustration (or motivation) to be experienced by the system participants having evaluated their performances against the time constraints. In reality, *Implicit performance goal* may continue to erode if there is a belief in the system that the set goal (*Stated goal*) is too high or impossible to reach in some given time horizon. These concepts are introduced in the following enhancements.

TIME HORIZON EFFECTS: FRUSTRATION, MOTIVATION AND POSSIBLE RECOVERY

The two essential enhancements in this model are the concepts of project *Time horizon* and accomplishment motivation (or frustration) that results from the participants' assessment of their performance against this time horizon. The project time horizon is taken as 200 days in the following simulation runs. *Time horizon* is a stock variable representing how many days left to the end of the project, starting at the initial horizon value, and depleting day by day (see Figure 9). One subtle feature of this *Time horizon* stock is that it does not quite deplete to 0; it stops when it reaches what we call '*Short term horizon*' taken as 12 days. The idea is that if the goal is reachable in just another 12 days, these twelve days are always allowed. (The *Short term horizon* will have an active role in the next enhancements and will be discussed in the following section). So the depletion rate of *Time horizon* is given by:

Time_horizon_depletion_rate =
IF *Time_horizon* > *Short_term_horizon* THEN 1 ELSE 0

Accomplishment motivation effect is a factor that represents the participants' belief that the stated performance goal is achievable within the *Time horizon*. To formulate this, we represent *Accomplishment motivation effect* as a decreasing function of *Remaining work and time ratio* as shown in Figure 10. *Remaining work and time ratio* is an estimate of how many days would be needed to close the gap between the current *State* and *Stated goal*, relative to the remaining *Time horizon*:

Remaining_work_and_time_ratio =
[(Stated_goal – Perceived_performance)/5]/Time_horizon

In the above formulation, the discrepancy between *Stated goal* and *Perceived performance* is first divided by the maximum rate at which *State* can be improved (which is *Maximum_capacity* – *Maximum_loss* = 15 – 10 = 5), yielding how many days would be needed at least to close the gap. (*Perceived performance* is just an exponentially smoothed average of *State*). The result is then divided by remaining *Time horizon* to provide a normalized ratio. (This ratio is also smoothed in the model, so that motivation does not change too fast, without any inertia). Figure 10 states that motivation is full (equal to one) when the above ratio is less than or equal to 0.7, it starts dropping afterwards and when the ratio becomes about 2, it denotes complete frustration (equal to zero).

Accomplishment motivation effect plays two different roles in the model. First, this motivation increases the effective improvement capacity of the participants:

$$Improvement\_capacity = Accomplishment\_motivation\_effect \times Maximum\_capacity$$

where $Maximum\_capacity = 15$

Thus, the more motivated the participants are, the closer becomes the actual *Improvement capacity* to *Maximum capacity*. (In the earlier versions of the model, *Accomplishment motivation effect* was set to 1, so it had no effect). This first role of *Accomplishment motivation effect* is represented by the positive feedback loop shown in Figure 11). The second role of *Accomplishment motivation effect* is to influence *Weight of stated goal* as follows:

$$Weight\_of\_stated\_goal = Accomplishment\_motivation \times Reference\_weight$$

where $Reference\_weight = 1.0$

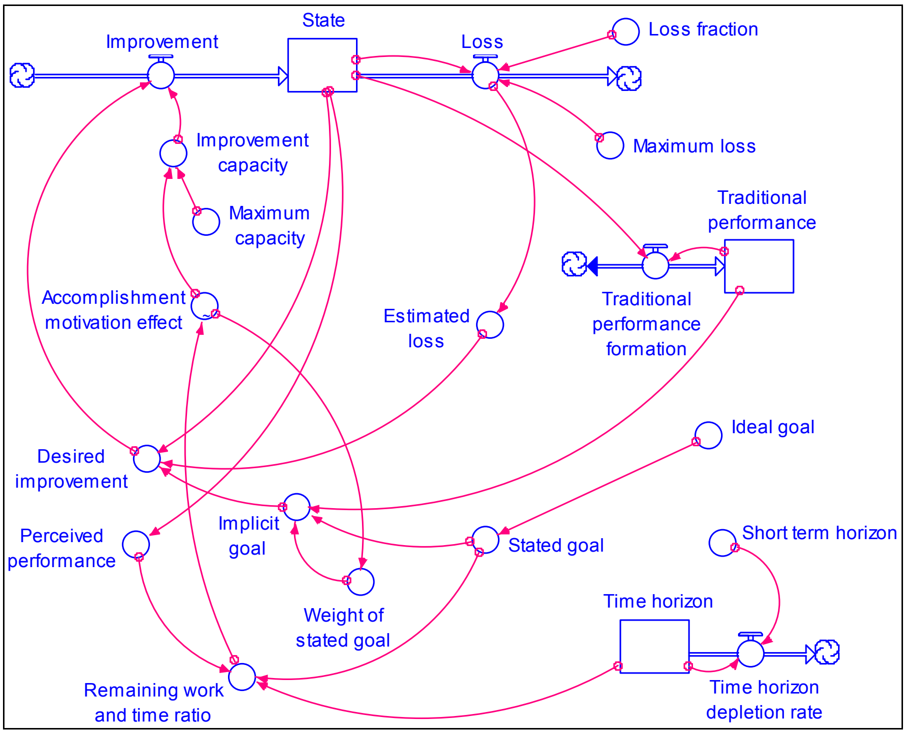

Figure 9. A model of goal erosion and possible recovery with a time horizon

Thus, *Weight of stated goal* is now a variable, depending on the motivations of the participants. When participants have full motivation (1.0), then *Weight of stated goal* becomes 1.0 as well, so that in forming their *Implicit goal, participants give* 100% weight to S*tated goal* and no weight at all to *Traditional performance.* At the other extreme, with zero motivation, all weight is given to *Traditional performance* and zero weight to S*tated goal* (meaning complete goal erosion). In between these two extremes, some non-zero weights are given both to S*tated goal* and to *Traditional performance*, depending on the level of motivation (see Figure 10).

Figure 10. *Accomplishment motivation effect* is a function of *Remaining_work_and_time_ratio*

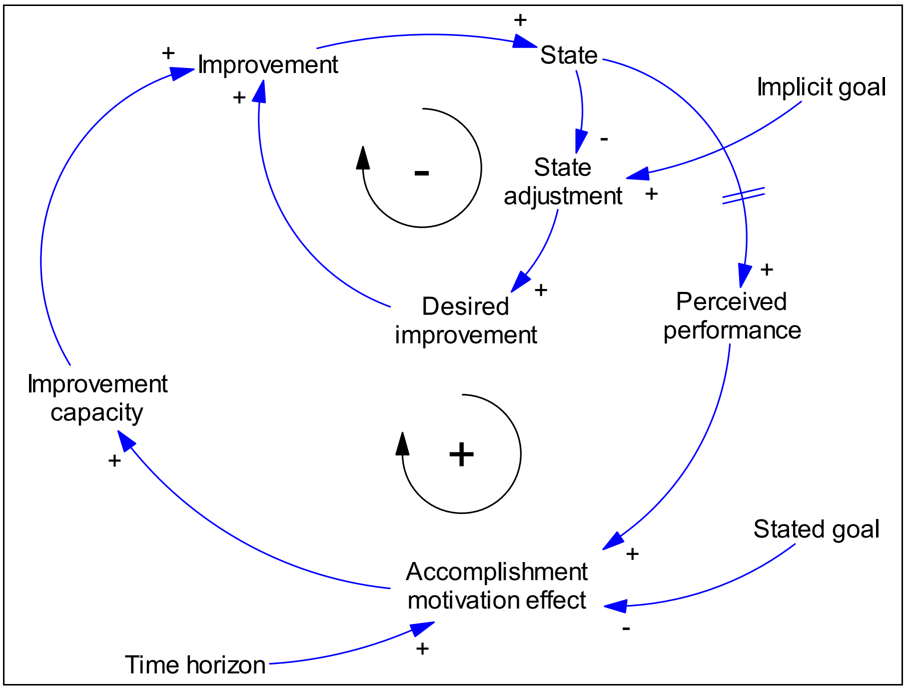

Figure 11. The *State* seeks the *Implicit goal*, via *Improvement* (the basic inner goal-seeking loop). Simultaneously, the *Perceived performance* relative to *Time horizon* determines the *Accomplishment motivation effect* which in turn affects the *Improvement* (the outer reinforcing loop).

Two typical dynamics generated by this model are depicted in Figures 12 and 13. In both dynamics, there is an initial phase of strong erosion in *Implicit goal*, because the *Stated goal* level is too high compared to the initial *State* (hence *Traditional performance*). After this initial erosion, the next phase is one of recovery: Implicit goal starts moving up gradually, and thus pulling up the *State* and *Traditional performance*. Finally, there is a third phase in the dynamics that is interesting: In Figure 12, all three variables, after having improved significantly, reverse their patterns and a final phase of erosion begins, continuing all the way to the end. The mechanism behind this final erosion is related to the time horizon of the project and the negative effects of de-motivation resulting from the impossibility of reaching the goal, given the time constraint. This is observed in Figure 12, where *Stated goal* is set to 1000 and *Time horizon* at 200. In Figure 13, on the other hand, *Stated goal* is set at a lower value of 750 and the second phase of erosion never takes place. The reason why all variables (*Implicit goal, State* and *Traditional goal*) continue to improve is that *Stated goal* is now set at a more 'realistic' value, relative to the given *Time horizon*. So the gap between *Stated goal* and *Perceived performance* relative to the remaining time horizon never becomes so high as to cause a hopeless situation for the participants. At the end, *State* can sustain a value of 750, which is below the *Ideal goal* of 1000, but much better than the 'giving up' dynamics of Figure 12.

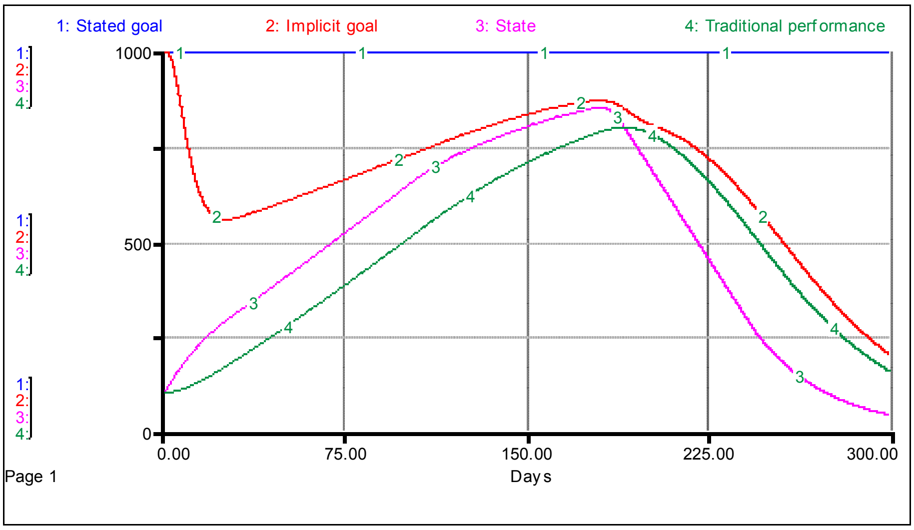

Figure 12. Erosion dynamics, when *Stated goal* is too high for the given *Time horizon* (*Stated_goal* = 1000, $Time\_horizon_0$ = 200)

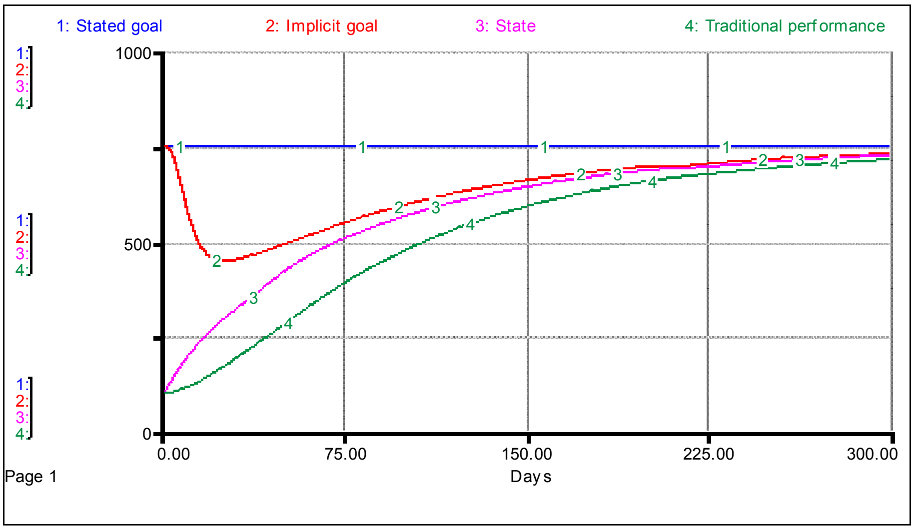

Figure 13. Erosion-then-recovery, when *Stated goal* is low enough for the given *Time horizon* (*Stated_goal* = 750, $Time\_horizon_0$ = 200)

ROLE OF SHORT-TERM HORIZON IN POTENTIAL RECOVERY

A second component of motivation may have to do with the participants' own intrinsic *Short term horizon*, (assumed to be 12 days). The assumption is that participants judge their own performance over a 12-day horizon and if they are satisfied (high *sort term motivation*), then they give more weight to the *Stated goal*, otherwise they lower this weight (meaning that the weight of their *Traditional performance* increases).

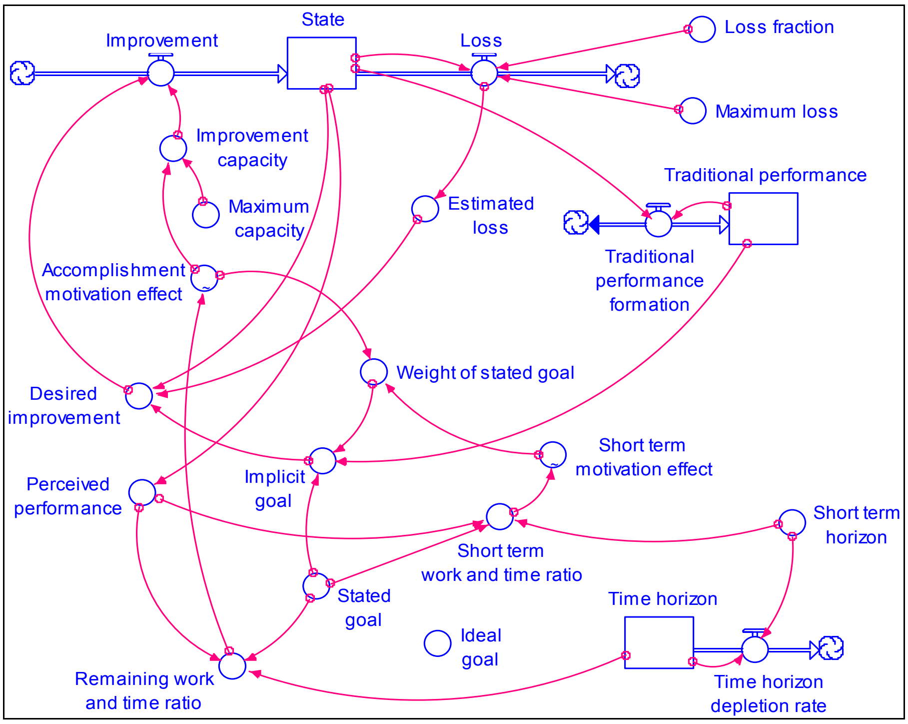

Figure 14. *Time horizon*, *Short term horizon* and their corresponding motivation effects

The new equation for *Weight of stated goal* becomes:

$$Weight\_of\_stated\_goal = Accomplishment\_motivation \times Short\_term\_motivation \times Reference\_weight$$

where $Reference\_weight = 1.0$

The formulation of *Short term motivation effect* is very similar to that of long term *Accomplishment motivation effect* described in the previous section: The motivation is a decreasing (from 1 down to 0) function of *Short term work and time ratio*, defined just like *Remaining work and time ratio* defined above, except that the ratio is divided by *Short term horizon* (12 days constant) instead of *Time horizon* of the project. One implication is that if participants perceive that only 12 days of full effort can take them to the goal, then they never give up, even if one day is left to the project *Time horizon*. Thus, the weight of *Stated goal* (hence potential erosion of *Implicit goal)* depends more subtly on the dynamics of both the short and long term accomplishment motivations of the participants. These long term and short term motivation interactions and main loops are shown in figure 15.

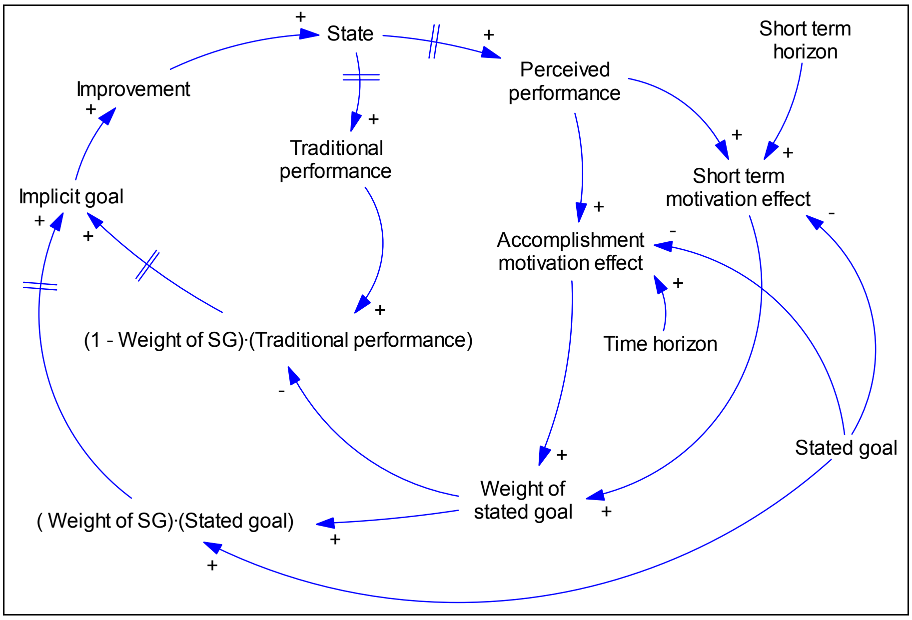

Figure 15. A weighted average of *Traditional performance* and *Stated goal* determines *Implicit goal* after some delay. The weight depends on the short term and long term accomplishment motivations, which in turn depend on perceived remaining performance gaps (relative to the time horizons)

As will be seen below, where the *Stated goal* is set turns out to be critically important in this new model. The dynamics for the different values of *Stated goal* are plotted in Figures 16, 17 and 18.

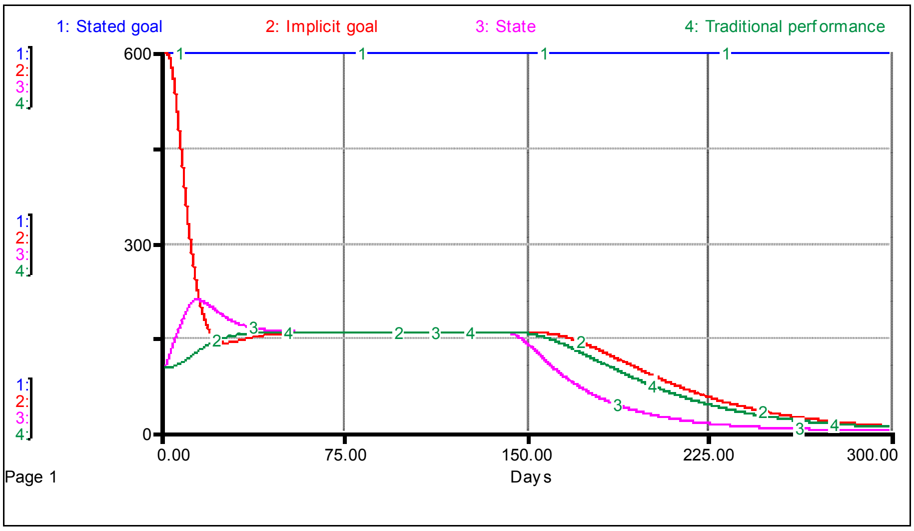

Figure 16. After an initial erosion in *Implicit goal*, long term stagnating *State* eventually results in giving-up behavior (*Stated_goal* = 600; *Time_horizon*$_0$ = 200)

If the *Stated goal* is too high (for instance 600) relative to the initial *State* (100) and *Time horizon* (200), there develops a disbelief in the system that the stated goal is ever reachable. This disbelief results in de-motivation, which further causes the *Weight of stated goal* to reduce to near zero and the *Implicit goal* erodes (Figure 16). After this initial eroding goal behavior, motivations never become high enough to ignite a performance improvement, but they can at least sustain the performance at some level for some duration of time. Finally, the system participants recognize that the remaining time to accomplish the *Stated goal* is impossibly too short, which results in 'giving-up' behavior and improvement activity eventually dies down (Figure 16).

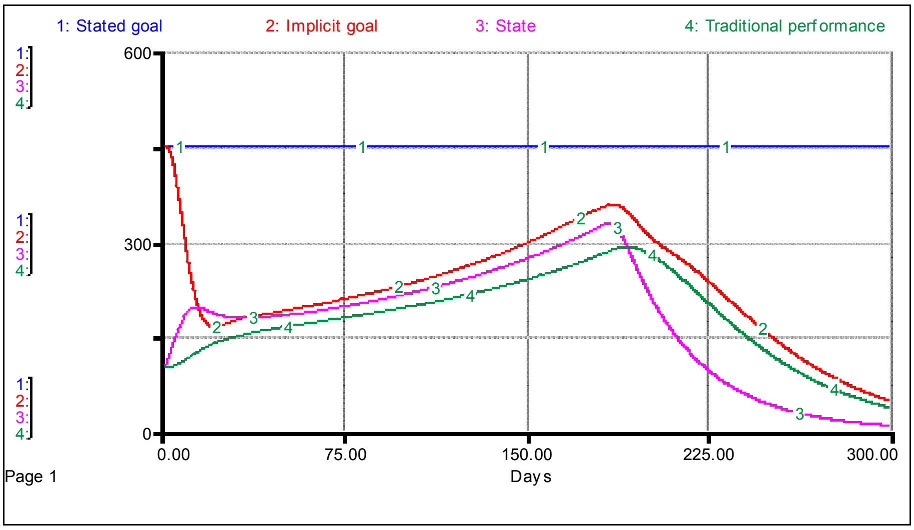

Figure 17. Initial erosion, then recovery and finally giving-up behavior due to time limit ($Stated\_goal$ = 450; $Time\_horizon_0$ = 200)

The next simulation experiment starts with a lower *Stated goal.* In Figure 17, firstly we observe an eroding goal behavior in the short term, due to the initial gap between *Stated goal* and *Traditional performance*. But because *Stated goal* is not too high (450), this time the *Weight of stated goal* does not become too small, which allows a goal recovery phase between days 50 and 175. But, still the *Stated goal* is not low enough to prevent a giving-up behavior in longer term due to the time limit. So, in Figure 17, three different stages of goal dynamics can be observed: initial goal erosion, goal (and state) recovery, and finally giving-up behavior.

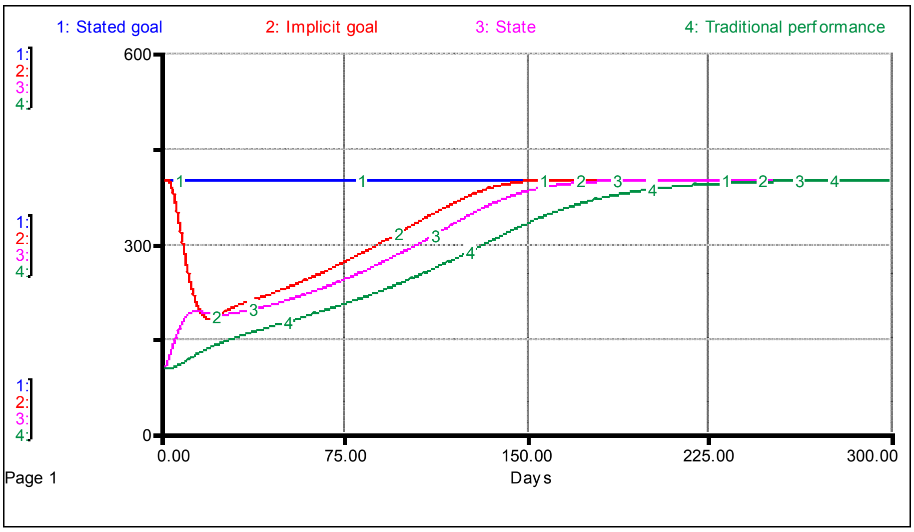

Figure 18. If *Stated goal* is low enough, sustainable recovery is possible ($Stated\_goal$ = 400; $Time\_horizon_0$ = 200)

Finally in Figure 18, *Stated goal* is low enough (400) to create a success: the recovery is sustained and the goal is reached in the given *Time horizon*. The three dynamics (Figures 16, 17 and 18) show that if *Stated goal* is low enough relative to initial *State* and *Time horizon* so as to create enough motivation, the *State* will improve towards the goal and achieve it.

But, how can a manager know the 'correct level' of the *Stated goal*? Furthermore, what if this level of performance is too low (conservative) compared to the true potential of the system participants? Our comprehensive model and simulation experiments so far illustrate these issues. As a result, we conclude that solutions to the above problems necessitate use of a "dynamic and adaptive goal setting" strategies by the management, as will be addressed in the next section.

ADAPTIVE GOAL SETTING POLICY FOR CONSISTENT IMPROVEMENT

J. W. Forrester (Forrester 1975) states: "…The goal setting is then followed by the design of actions which intuition suggests will reach the goal. Several traps lie within this procedure. First, there is no way of determining that the goal is possible. Second, there is no way of determining that the goal has not been set too low and that the system might be able to perform far better. Third, there is no way to be sure that the planned actions will move the system toward the goal."

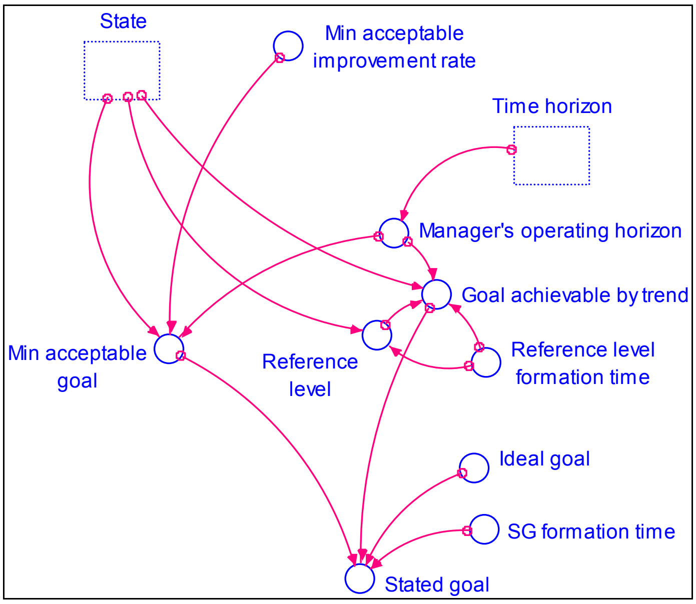

Figure 19. Proposed adaptive dynamic *Stated goal* setting policy structure

In order to address these uncertainties, *Stated goal* should be set and managed dynamically and adaptively. The management must continuously monitor the *State* and must evaluate its level and its trend. The *Stated goal* should be then set realistically within the bounds of a "reachable region", which is a function of the *State level* and its trend (net improvement rate). If *State* is improving, *Stated goal* must also be gradually moved up to guide and motivate the improvement activities. On the other hand if the *State* is stagnating, this means that *Stated goal* is unrealistically high, so it must be lowered till there is a sign of sufficient improvement in the *State* level. The structure in Figure 19 is designed to implement and test such an adaptive management strategy.

In the related formulations, we assume that top management does not know *Implicit goal*, *Weight of stated goal*, the *motivation effects*, *Short time horizon*, *Capacity* and *Loss flow*. Management can only perceive the system performance (*State*) over time, so the *Stated goal* decisions must be based on this information. If *State* is not improving enough, *Stated goal* should be lowered, and if *State* is improving then *Stated goal* must also be gradually moved up. Beyond this, exactly how much *Stated goal* should be moved up or down, depends on several factors: *Stated goal* can not be bigger than *Ideal goal* and it should not be lower than some minimum acceptable goal determined by the top management. If the level determined by the *trend* in *State* is in acceptable region, then *Stated goal* must be equal to this level:

$$Stated\_goal = \\ MIN(Ideal\_goal, MAX(Goal\_achievable\_by\_trend, Min\_acceptable\_goal))$$

Ideal goal is a given constant (1000) as discussed earlier. The second variable, *Goal achievable by trend* is a managerial estimate of the current improvement trend and what level can be attained at this rate, in some time horizon:

$$Goal\_achievable\_by\_trend = State + \\ ((State - Reference\_level)/Reference\_level\_formation\_time)\times \\ Manager's\_operating\_horizon$$

$$Reference\_level = SMTH3(State, Reference\_level\_formation\_time)$$

$$Manager's\_operating\_horizon = MIN(90, Time\_horizon)$$

In the above formulation, *Reference level* is an average of past *State*, used in estimating the trend, by dividing the improvement by *Reference level formation time. Manager's operating horizon* is used in extrapolating the trend into the future. This horizon is equal to the time horizon of the project as the project advances. But in early phases, the managerial horizon is set to a smaller value (90), because it is assumed that extrapolating the current trend farther into the future would be too uncertain. Finally, the third component of Stated goal equation is some minimum acceptable goal determined by the top management. This *Min acceptable goal* is determined by adding some minimum acceptable improvement rate (in *Manager's operating horizon)* on top of the current *State*. It is assumed that a given management has some minimum acceptable improvement rate, below which is simply unacceptable:

$$Min\_acceptable\_goal = \\ State + Min\_acceptable\_improvement\_rate \times Manager's\_operating\_horizon$$

$$Min\_acceptable\_improvement\_rate = 0.5$$

In the above formulation, managerial constants like *Manager's operating horizon*, *Min acceptable improvement rate*, and *Reference level formation time* are set at some reasonable values that serve our research purpose. In an actual study, these constants must be well estimated by data analysis and interviews and also tested by sensitivity analysis.

The adaptive goal setting policy structure is integrated in the full model (of Figure 14) and simulation experiments are run under different scenarios. In all scenarios, it is assumed that management starts with a rather high initial *Stated goal* (900), to demonstrate the fact that the starting stated goal is not important anymore, because *Stated goal* is a variable in the adaptive goal setting policy. In figure 20, the provided *Time horizon* is quite short (200), so the expected behavior, based on previous experiments is one of strong erosion and give-up behavior towards the end (for instance, Figures 16 and 12). But the dynamics in Figure 20 display an obvious improvement: Initially, *Stated goal* is deliberately lowered (with some oscillations) by top management so as to ignite participant motivation, and then later it is moved up gradually and adaptively, pulling together with it the *Implicit goal* and *State*. At the end, although reaching the ideal goal of 1000 was impossible in the given *Time horizon*, *State* has improved to a reasonable level (500) within the time limits, without displaying any giving-up behavior.

In the second experiment, a longer *Time horizon* (350) is provided. The main dynamic characteristics are the same as those observed in the previous run: *Stated goal* is deliberately lowered initially by top management, and then later, it is moved up gradually and adaptively, pulling together the *Implicit goal* and *State* (Figure 21). At the end, since the *Time horizon* is longer, *State* is improved to a higher level (750), compared to the previous run (although still lower than the ideal goal of 1000). From these two runs, the important contribution of the adaptive goal setting policy is obvious: The performance consistently improves and eventually settles down at a level without any giving-up behavior at the end, which apparently is a strong improvement within the given *Time horizon*.

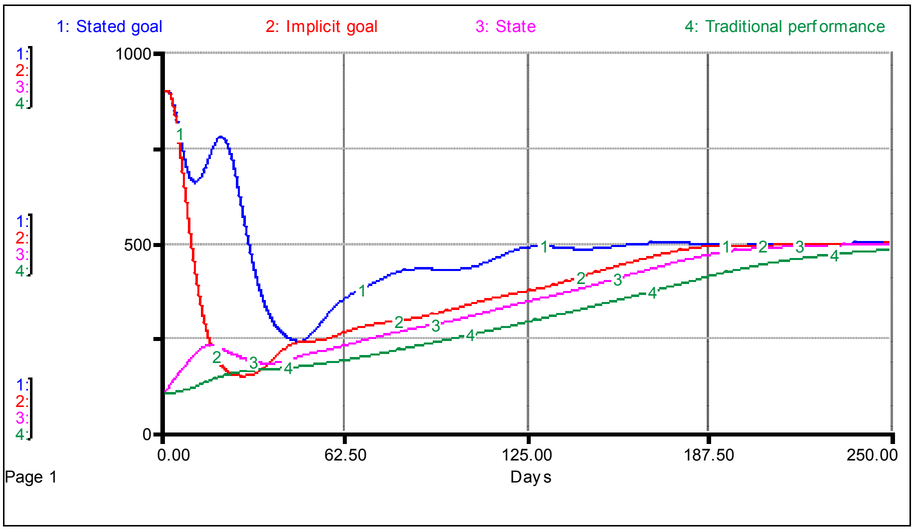

Figure 20. A satisfactory result with the dynamic goal management policy, even when the initial *Stated goal* is high (900) and *Time horizon*$_0$ is short (200)

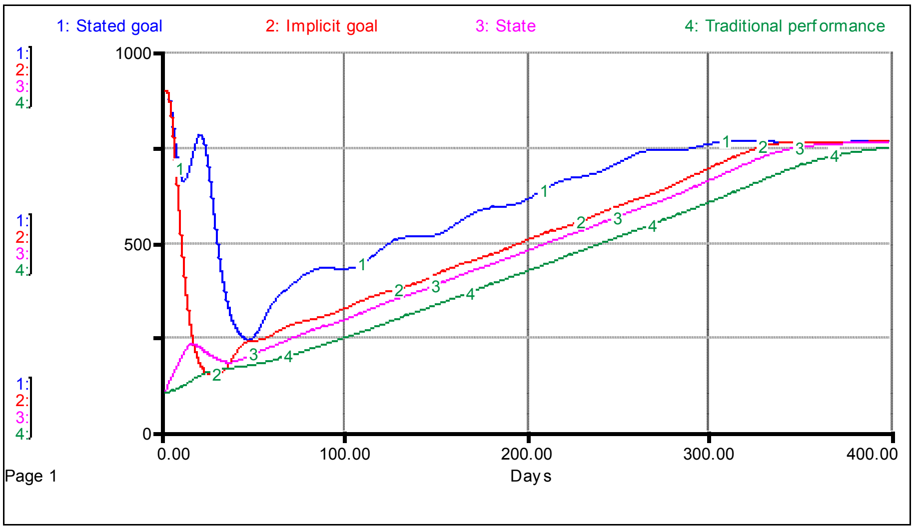

Figure 21. A better result with dynamic goal management policy, when more time is provided (initial *Stated_goal* = 900 & $Time\_horizon_0$ = 350)

Finally, when *Time horizon* is sufficiently long relative to the *Ideal goal* of the project, the last simulation experiment demonstrates that *Ideal goal (1000)* can be reached. In Figure 22, *Time horizon* is taken as 500 and we observe that with sufficient time, the *Ideal goal* is eventually attained within the program *Time horizon*, implying maximum organizational success.

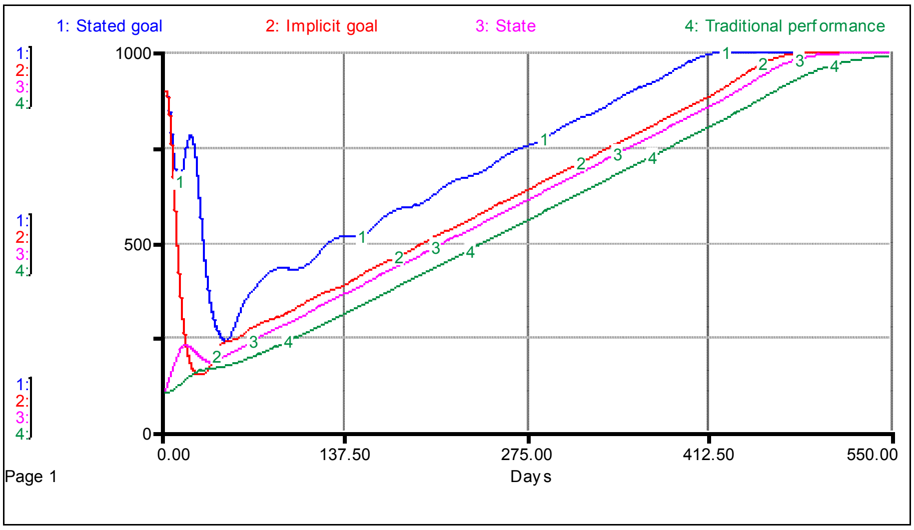

Figure 22. A close optimal result*: Ideal goal* is attained via dynamic goal management, when *Time horizon* is long enough (initial *Stated_goal* = 900 & $Time\_horizon_0$ = 500)

CONCLUSIONS

In the simplest computer/simulation models of goal-seeking in organizations, there is a constant goal and the model describes the dynamic difficulties involved in reaching that given goal. In more sophisticated models, the goal itself is variable: it can erode as a result of various phenomena such as frustration due to persistent failure or it can evolve further as a result of confidence caused by success. There exist some models of limited and linear goal erosion dynamics in the literature. We extend the existing models to obtain a comprehensive model of goal dynamics, involving different types of explicitly stated and implicit goals, expectation formation and potential goal erosion as well as positive goal evolution dynamics. The model constitutes a general theory of goal dynamics in organizations; involving a host of factors not considered before, such as organizational capacity limits on performance improvement rate, performance decay when there is no improvement effort, time constraints, pressures, and motivation and frustration effects. We show that the system can exhibit a variety of subtle problematic dynamics in such a structure.

We build a series of more and more realistic and complex goal-related structures. The purpose of each enhancement is to introduce and discuss a new aspect of goal dynamics in increasingly realistic settings. In the first enhancement, we introduce how the implicit goal in an organization may unconsciously erode as result of strong past performance traditions. Next, we discuss under what conditions recovery is possible after an initial phase of goal erosion. In the following enhancement, we include the effects of time constraints on performance and goal dynamics. We also show that in such an environment, the implicit short-term self-evaluation horizons of the participants may be very critical in determining the success of the improvement program. Finally we propose and test an adaptive goal management policy that is designed to assure satisfactory goal achievement, by taking into consideration the potential sources of failures discovered in the preceding simulation experiments.

Our theoretical model and management strategies can be implemented to specific improvement program settings, by proper adaptation of the model structures and calibration of parameters. Several managerial parameters in our models are set at some reasonable values that serve our research purpose. In further applied research and actual studies, these constants must be well estimated by data analysis and interviews and also tested by sensitivity analysis. Our models can also be turned into interactive simulation games, microworlds and larger learning laboratories so as to provide a platform for organizational learning programs. More generally, our models may provide useful starting points for different research projects on goal setting, performance measurement, evaluation and improvement.

REFERENCES

Barlas, Y., 2002, System Dynamics: Systemic Feedback Modeling for Policy Analysis, in *Knowledge for Sustainable Development: An Insight into the Encyclopedia of Life Support Systems*, UNESCO Publishing – Eolss Publishers (Paris, France; Oxford, UK), pp. 1131-1175.

Barlas, Y. and M. G. Özevin, 2004, “Analysis of Stock Management Gaming Experiments and Alternative Ordering Formulations”, *Systems Research & Behavioral Science,* Vol. 21, Issue 4, pp. 439-470.

Barlas, Y. and H. Yasarcan. 2006, Goal Setting, Evaluation, Learning and Revision: A Dynamic Modeling Approach, *Evaluation and Program Planning*, Vol. 29, Issue 1, pp 79-87.

Ericsson, K. A., 2001, Attaining Excellence Through Deliberate Practice: Insights from the Study of Expert Performance, in M. Ferrari (ed.), *The Pursuit of Excellence in Education*, Erlbaum (Mahwah, NJ), pp. 21- 55.

Ford, A., 1999, *Modeling the Environment*. Island Press (Washington, DC).

Forrester, J. W., 1961, *Industrial Dynamics*, MIT Press (Massachusetts).

Forrester, J. W., 1975,. Planning and Goal Creation: Excerpts, in *Collected Papers of Jay Forrester*, Wright-Allen Press (Massachusetts), pp. 167-174.

Forrester, J. W., 1994, Policies, Decisions, and Information Sources for Modeling, in J. D. W. Morecroft & J. D. Sterman (eds.), *Modeling for Learning Organizations*, Productivity Press (Portland, Ore.), pp 51-84.

Lant, T. K., 1992, Aspiration Level Adaptation: An Empirical Exploration, *Management Science*, Vol. 38, Issue 5, pp. 623-644.

Lant, T. K., & Mezias, S. J., 1992, An Organizational Learning Model of Convergence and Reorientation, *Organization Science*, Vol. 3, pp.47-71, (reprinted in Cohen, M. D. & Sproull, L.S. (eds.), 1995, *Organizational Learning*, Sage Publications).

Morecroft, J. D. W., 1983, System Dynamics: Portraying bounded rationality. *OMEGA The International Journal of Management Science*, Vol. 11, Issue 2, pp. 131-142.

Morecroft, J. D. W., & Sterman, J. D. (eds.), 1994, *Modeling for Learning Organizations*, Productivity Press (Portland, Ore.).

Newcomer, K., & Neill, S. (Eds.), 2001, Assessing Program Performance: Measurement and Evaluation, special issue of *Evaluation and Program Planning,* Vol. 24, Issue 1.

Roberts, E. W., 1981, *Managerial Applications of System Dynamics*, MIT Press (Cambridge, Massachusetts).

Schalock, R. L., & Bonham, G. S., 2003, Measuring Outcomes and Managing for Results, *Evaluation and Program Planning*, Vol. 26, Issue 3, pp. 229–235.

Senge, P. M., 1990, *The Fifth Discipline: The Art and Practice of the Learning Organization*, Currency and Doubleday (New York).

Simon, H., 1957, *Administrative Behavior: A Study of Decision Making Processes in Administrative Organizations*, Macmillan (New York).

Spector, J. M., & Davidsen, P. I., 2000, Cognitive Complexity in Decision Making and Policy Formulation: A System Dynamics Perspective, in R. Sanchez & A. Henee, *Selected Papers from the 4th International Conference on Competency Based Management*.

Spector, J. M., Christensen, D. L., Sioutine, A. V., & McCormack, D., 2001, Models and Simulations for Learning in Complex Domains: Using Causal Loop Diagrams for Assessment and Evaluation, *Computers in Human Behavior*, Vol. 17, pp. 517-545.

Sterman, J. D., 1987, Expectation Formation in Behavioral Simulation Models, Behavioral Science, Vol. 32, pp. 190-211.

Sterman, J. D., 1989, Modeling Managerial Behavior: Misperceptions of Feedback in a Dynamic Decision Making Experiment, Management Science, Vol. 35, No. 3, pp. 321-339.

Sterman, J. D., 2000, *Business Dynamics: Systems Thinking and Modeling for a Complex World*, McGraw-Hill (New York).

Yasarcan, H., 2003, *Feedback, Delays and Non-linearities in Decision Structures*, Ph.D. Thesis, Bogazici University.

Yasarcan, H., & Barlas Y., 2005, A Generalized Stock Control Formulation for Stock Management Problems Involving Composite Delays and Secondary Stocks. *System Dynamics Review*, Vol. 21, Issue 1, pp. 33–68.