# On Retaining Extreme Value Outcomes in an Aging Chain With a Co-Flow Structure

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## Summary

In many situations, System Dynamics modelers have to capture attributes of items tracked in an aging chain. Typically, the outflow of items from the stocks in these chains depends on the attributes tracked in the co-flow. However, these well known, classic models fail to account for a specific phenomenon - the screening of items. This study presents a new application of co-flows in aging chains: A co-flow that enables the process of screening, i.e. the process of either terminating or approving items, depending on an attribute. We model a two-stage aging chain with a co-flow structure that tracks the number of items *and* their related attributes. Managers at each stage must decide on capacity utilization of workforce and thresholds for minimum attribute values.

The model structure presented here could have many applications, such as new product development (NPD) pipelines and other situations in which items go through a sequence of stages and are screened, depending on a specific attribute (Net Present Value in case of NPD pipelines).

There are some key structures endogenous to the process of screening, namely 1) Capacity adjustment (how the throughput of items will be adjusted), 2) Type of screening (minimum or maximum values can be selected according to the distribution of the population of attributes) and 3) Relation between co-flow attribute and throughput. This last structure determines if changes in the co-flow attribute from one stage to the next will be affected by capacity utilization, i.e. by how intensively resources (people) are used, affecting the throughput. For example, in product development pipelines it is generally assumed that projects gain value as they are developed and taken to the next stage, and that the level of value gain depends on how intensively project teams are working (Wheelwright and Clark, 1992, pg. 91, Girotra *at al,* 2005). Attributes tracked in a co-flow are also affected by the screening process itself since some attribute is lost owing to the termination of items. For instance, by selecting only items with high attributes, the average attribute of the surviving population of items is increased.

We study the structure of the screening problem by formulating a System Dynamics model that tracks the number of items and their attributes at each stage within a co-flow structure. We model the screening process by applying an extreme value probability distribution function (PDF) to the population of attributes of items at each stage. These items are eliminated or approved depending on the percentage of items below or above a pre-determined threshold. A detailed explanation about the extreme value PDF is found in section 3.

Such model allows us to explore the question of how the screening process should be developed to account for the successive selection of the items with higher attributes. Implications of the new system dynamics structures are discussed in the final section.

## 1. Introduction

In many situations, System Dynamics modelers have to capture attributes of items tracked in a chain. Such attributes might include average experience, age and skill of a workforce or population, quality of materials, or energy and labor requirements of a firm's machine (Sterman, 2000). Typically, the outflow of items from the stocks in these chains depends on these attributes that are tracked in the co-flow. For instance, the rate at which people replace their cars depends on the age of the cars, and machine breakdowns in a plant depend on the time the machine was last overhauled. These are examples of aging chains. In such chains, items flow from one stock to the next: there is a disaggregation of a (first-order) material delay into an nth-order one, where each outflow from sub-material-delay flows into the next sub-material-delay.

Aging chains are used to represent situations in which items go through a sequence of stages, such as different degrees of work experience, age groups, and categories of housing and employment. People and items "travel" through these groups or stocks. However, these well known, classic models of aging chains with co-flows fail to account for a specific phenomenon - the **screening** of items. Instead of having all items flow from one stage to another without any exclusion, it is certain that in many situations, part of the population of items in a stock is screened at pre-determined points of the chain, and are either eliminated or taken to the next stage. Screening is the process of selecting items in a stockwhere the items are evaluated according to an attribute or attributes that define their performance or adequacy, and then are either taken to the next stock of the chain or eliminated.

This study presents a new application of co-flows in aging chains: A co-flow that enables the process of screening. The model structure presented here could have many applications, such as product development pipelines and other situations in which items go through a sequence of stages and are screened, depending on a specific attribute. Table 1 presents a list of possible applications to be explored. Such list is not exhaustive and some of the characteristics have not been validated, especially the way the attribute in the co-flow changes from one stage to the next. We focus on items moving into a next stage in case they have a *minimum* threshold (so that the surviving population of items has higher attributes), but other configurations are possible. For example, in some cases items can be selected for having attribute values up to a *maximum*. This should be the case of maintenance of machines where minimum compliance quality determines which machines will continue the process. In other cases, distribution of attributes might be normally distributed; that could be the case of supply chains of perishable goods, for example. Also, in the healthcare industry, the treatment of chronic patients might not have a formal screening process, but there is an exit flow of items (patients) due to death as a function of a "health index".

We focus on screening based on a single attribute across the entire pipeline, but in theory it is possible to create a screening process that takes into account multiple attributes, i.e. different attributes for different stages. That would demand multiple coflows or a single, weighted coflow. For example, a pharmaceutical company might be more concerned with the value (NPV) of a substance at the early stages and with safety at later stages.

Even though there is a number of variables affecting co-flow attributes (for example, in product development pipelines, availability of technologies affects how much value is added to projects), capacity utilization is a key variable in this regard as it not only may affect the quality, performance or value of different kinds of items, but also determine the flow of items in the pipeline. Capacity utilization is defined as a measure of work intensity, or how many simultaneous tasks workers are assigned to.

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Figure 1 shows a classic example of the use of a Co-flow with the purpose of tracking labor requirements in a firm's capital stock (Sterman, 2000). Figure 2 presents a similar configuration. However, it is adapted to the product pipeline management (PPM) process. In such process, **screening** is present. The figure demonstrates the simplest configuration of screening in an aging chain, i.e. a single-stage model with co-flow. This simplified representation shows how items (projects) are initiated, developed and moved to the review stock, in which they are evaluated and either completed and taken to the next stage, or terminated. While projects are being developed, value creation is happening in the co-flow. Such value (an attribute) accumulates in the "Value in Stage 1 Review" stock, and is either lost or transferred to the next stage along with its corresponding projects.

In order to know which fraction of the stock of items and of the stock of value shall have to be terminated, it is necessary to know which percentage of items has a value lower than the pre-determined threshold. While calculating such percentage, assumptions have to be made on how the population of values of items is distributed, i.e. what the probability distribution function (PDF) of the attributes is. The choice of different thresholds will result in a different percentage of projects that are accepted. A higher threshold will necessarily reduce this fraction.

Table 1: Different processes enabled by screening, selecting maximum values

| **Context** | **Main Stock** | **Co-Flow Attribute*** ** | **Type of Screening**** | **Attribute Change*** | **Impact of screening on average attribute of surviving population** | **Objective of System Dynamics Analysis** |
|---|---|---|---|---|---|---|
| New Product Development | Projects | Net Present Value | Maximum Value (Gumbel) | +, dependent on utilization | + | PPM Policies (resource, capacity and project complexity allocation) |
| Financial Services Pipeline | Loans | Conformance index | Maximum Value (Gumbel) | +, independent on utilization | + | Dynamic Capacity management, resource allocation |
| Closed Loop Supply Chains | Supplies | Overall Quality | Maximum Value (Gumbel) | n/a | + | Manage returned items across chain, Capacity planning, Refurbishment viability (fixed costs) |

| | | | | | | |
|---|---|---|---|---|---|---|
| HR Training Pipeline | Personnel | Qualification & Performance index | Maximum Value (Gumbel) | +, dependent on utilization | + | Improvement of overall workforce qualification |
| Training High-Risk Career (e.g., Soldier) | Personnel | Qualification & Performance index | Maximum Value (Gumbel) & additional exit flow (death) | +, dependent on utilization | + | Improvement of overall workforce qualification and longevity |
| Production Line (high scrap rate) | Products | Quality index | Maximum Value (Gumbel) | +, dependent on utilization | + | Capacity/Complexity Management to reduce scrap rate |
| Natural Selection of Species | Living Beings | “Adaptation Index” | Maximum Value Gumbel +in/out flow (death & births) | n/a | + | Evolutionary Biology dynamics, stages of environmental change (e.g. ice age). Scenario Analysis |
| ideas or beliefs transmitted from one person or group to another | Units of Social Information (Memes) **** | Success Index: response to selective pressures | Maximum Value Gumbel +in/out flow (death & births) | +/- depending on how adaptation occurs | + | Dynamics of Cultural Evolution. Scenario Analysis. |
| Macro Organizational Behavior (OB) | Companies | Adaptability index | Maximum Value gumbel | +/-, depending on adaptation measures | + | Dynamics of Macro OB. Effects of environmental changes (regulations, economic crises etc). Scenario Analysis. |
| Infectology | Microorganisms | Resistance to drug index | Maximum value gumbel | +/-, depending on mutation | + | Development of Resistant bacteria/viruses |

*How the attribute in the co-flow changes from one stage to the next. “+” means positive change. “–“ means negative.

** See section 3.4 for a discussion on probability distribution functions for the population of items. A maximum Gumbel distribution occurs when items are selected for having a minimum threshold so that the population of items has maximum attribute values.

*** For certain configurations, more than one attribute coflow may be necessary

**** See “The Sellfish Gene”, by Richard Dawkins (1976),Oxford University Press.

Figure 1: Coflow to track labor requirements in a firm's capital stock (Sterman, 2000)

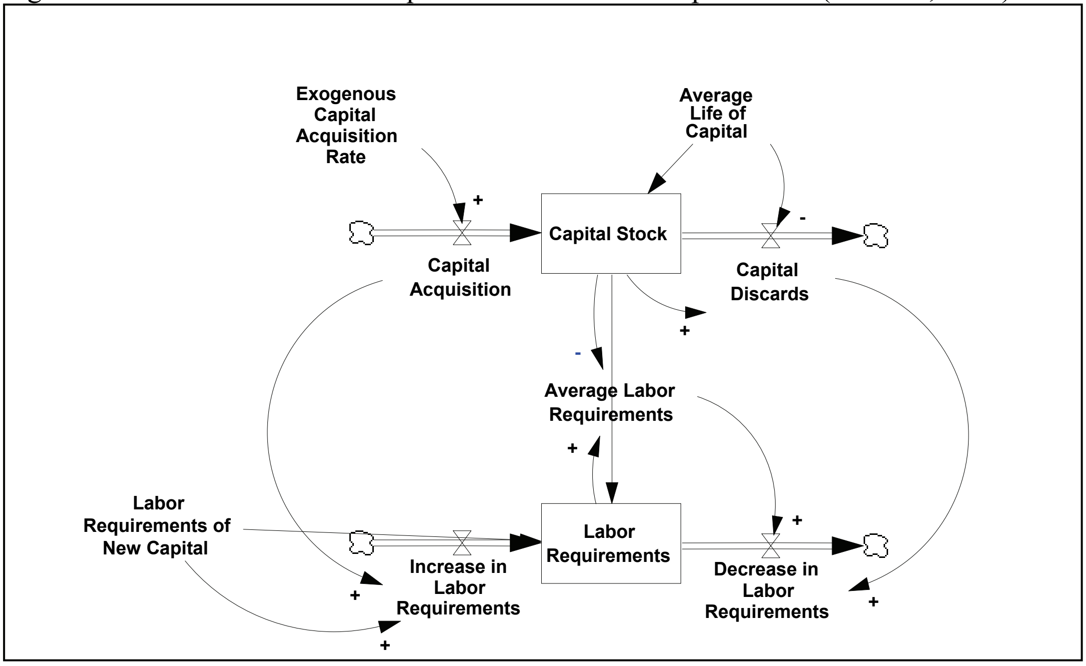
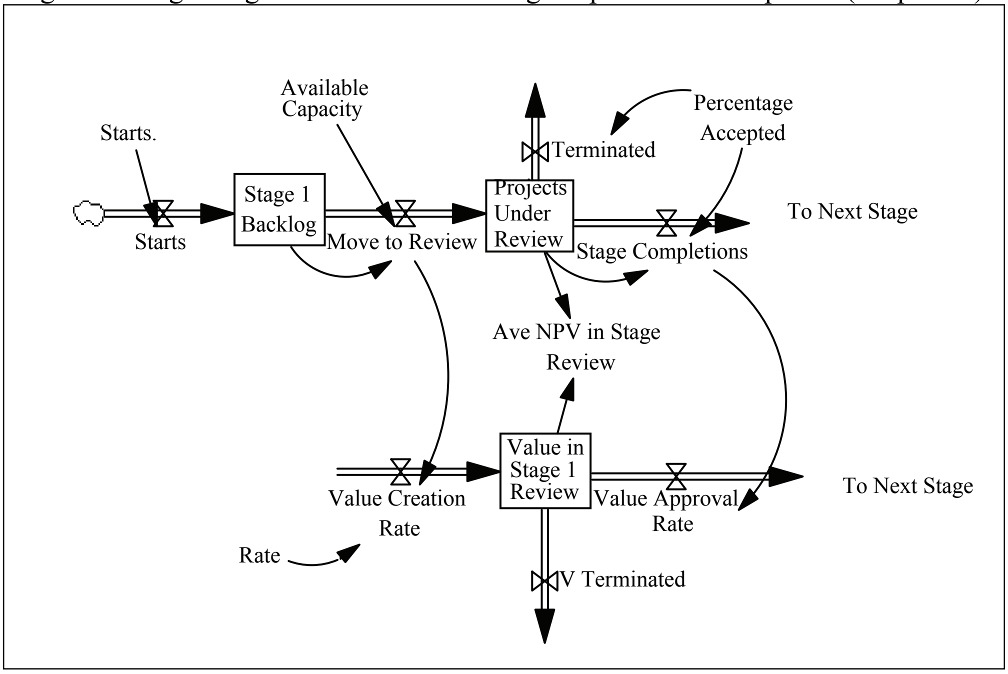



Figure 2: Single stage coflow with screening for product development (simplified)

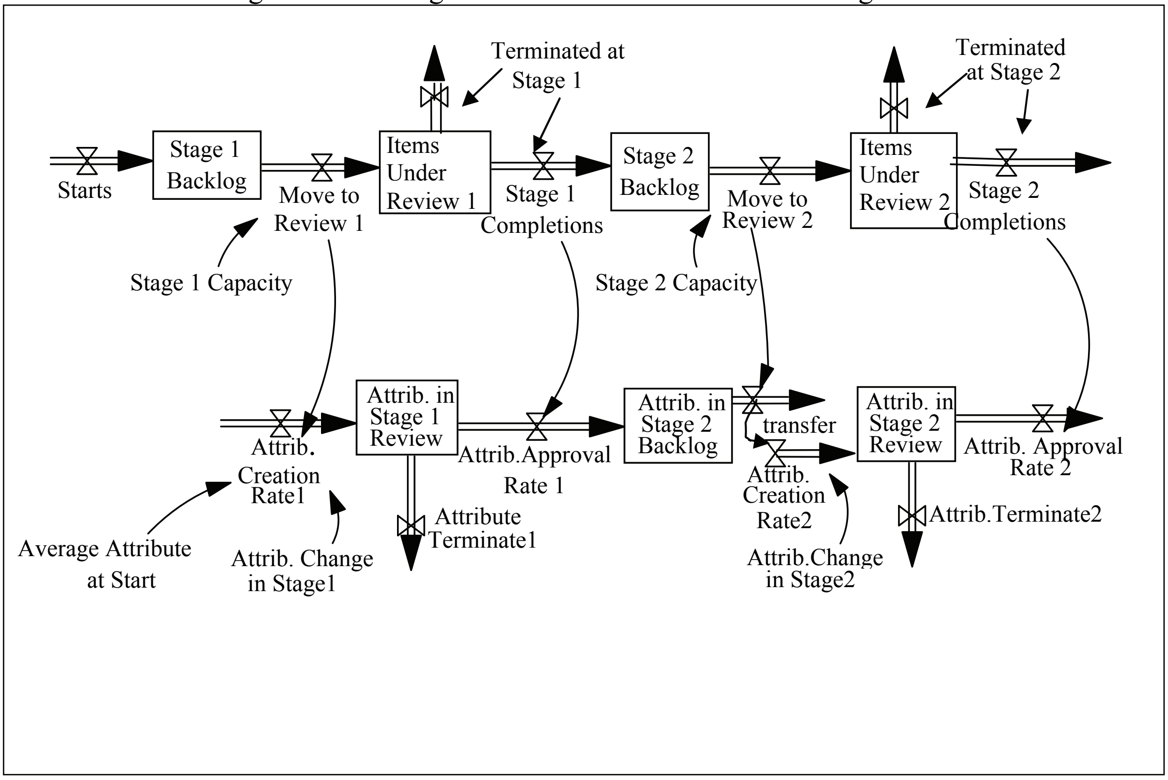



## 2. Model Structure and Use

We study the structure of the screening problem by formulating a System Dynamics model that tracks the number of items and their attributes at each stage within a co-flow structure. We model the screening process by applying an extreme value probability distribution function (PDF) to the population of attributes of items at each stage. These items are eliminated or approved depending on the percentage of items below or above a pre-determined threshold. A detailed explanation about the extreme value PDF is found in section 3.4 .

Such model allows us to explore the question of how the screening process should be developed to account for the successive selection of the items with higher attributes. Implications of the new system dynamics structures are discussed in the final section.

Figure 3: Tracking the Creation of Value in a Two-stage Co-flow




## 3. Model Description

For parsimony, our model incorporates only two stages as shown in figure 3. Outcome variables of interest are the total attribute created and the average attribute created at the end of the pipeline. The independent variables in our model are: number of items introduced into the pipeline, minimum acceptable attribute at each stage (thresholds 1 and 2) and managerial biases while adjusting capacity. A list of the units for the variables with pre-determined, fixed values is available in the appendix. Stocks on the main flow represent populations of items, and rates are measured in items per unit of time. Correspondingly, stocks on the attribute co-flow represent populations of attributes, and rates are measured in attributes per unit of time.

The model structure can be divided into three basic processes: capacity management, screening and attribute creation (the relation between co-flow attribute and throughput). Such key processes determine the flows in the pipeline, the performance or attribute measures and the selection of items. These are described next.

### 3.1 Capacity Management Process

A central construct of the model is the utilization of capacity. An important assumption in the model is that managers have, at each stage, a fixed amount of resources (employees). An increase in capacity is only possible by using the existing resources more intensively, thereby increasing their utilization. The significance of such formulation is that, in certain settings, changes in capacity utilization have been shown to affect attribute performance, such as in product development. The value of projects, measured by net present value (NPV), is a key attribute in the screening of projects. In other processes, such as services, human resources training, or production lines, similar effects may be at work. The basic idea is that there is an optimal level of capacity utilization that enhances the level of attributes at each stage. If employees work more or less intensively than such value, the increase in attributes will be diminished or reversed.

A more comprehensive capacity management process would incorporate overtime and hiring, but even in such setting, it would be reasonable to assume that an increase in capacity would have some impact on utilization. Our formulation for the capacity adjustment process is based on Anderson and Morrice's (2005) model, but adds a behavioral aspect to it. These authors studied the capacity adjustment of service providers. In such case, capacity is adjusted continuously, increasing or decreasing as necessary, depending on the inflow of items to the pipeline. If more items are introduced for a certain period, capacity utilization is increased so that items are processed quickly.

In our formulation, the available capacity of development teams is frequently adjusted , in order to either adapt to the work demand of each stage of the chain *or* to keep the utilization level around its nominal, normalized value (100%). This is the utilization level in which attribute creation rate is optimal. The process is defined here as "capacity adjustment bias", which represents a *tendency* of managers to either work faster to reduce backlogs of items or work at the capacity utilization that improves attribute creation.

Utilization is therefore calculated according to equation 1. In case of overcapacity, utilization is equal to the demanded capacity based on the backlog. It is assumed that there is a nominal (minimum) development time for any group of items, as formulated by Anderson and Morrice (2005).

$$\text{Utilization} = \frac{\text{MIN}\left(\dfrac{\text{Stage Backlog}}{\text{Nominal Dev Time}}, \text{Available Capacity}\right)}{\text{Nominal Capacity}} \qquad (1)$$

Change in Capacity is modeled as a first order exponential adjustment of Capacity toward Target Capacity with a Time to Adjust Capacity. We define target capacity as the weighted average of the nominal capacity (a capacity that yields the peak attribute creation) and the demanded rate of items in each stage based on the backlog.

$$\text{Target Capacity} = \frac{\alpha * \text{Stage Backlog}}{\text{Nominal Dev Time}} + (1 - \alpha) * (2 - \text{Utilization}) * \text{Nominal Capacity} \qquad (2)$$

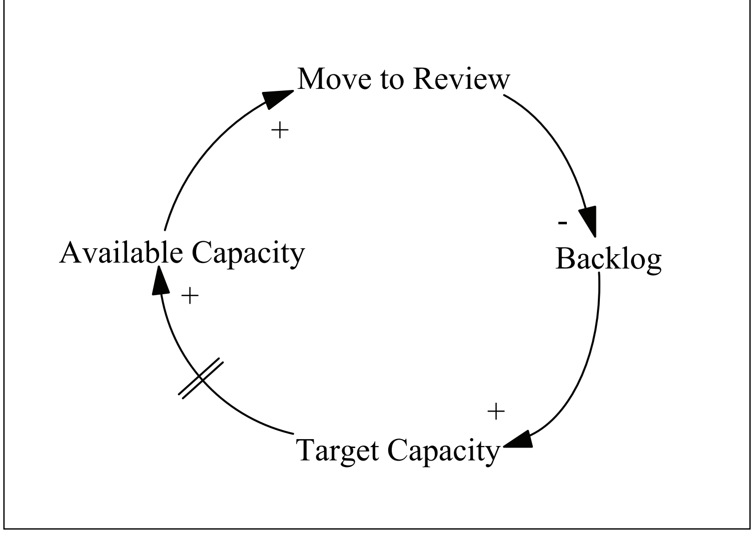
Here $\alpha$ is the manager's capacity adjustment bias, or bias towards reducing backlog ($0< \alpha<1$). Other formulations for target capacity are possible and would result in different convergence rates: the term (2-utilization) has the generic form (x-utilization), where x is equal to 1 if a linear weighted average is adopted. A larger X means that management temporarily inflates the target to a value higher than the "real" one in order to reach the desired capacity more quickly. Inflating of goals is a common phenomenon (Baumeister et al. 1993) found in different managerial settings, such as in supply chain ordering (Gonçalves, 2007).

Other formulations for the capacity adjustment process are possible. It may be desirable to mimic a company's current managerial policies and test for their efficacy. For example, managers might *anchor* their present target capacity on previous ones, or on a fixed benchmark. In such case, the previous value or benchmark would have a partial or full effect on target capacity. Capacity adjustment can also be formulated as a gradual adjustment with feedback. In such case, capacity would be constantly adjusted in steps, from a low or high value, until an optimal or near optimal performance is obtained. However, delays in the co-flow make this heuristic quite difficult to implement and it might create oscillations in the chain. Managers could also *forecast* the demands for capacity and use a time series to determine a target capacity at each time period. Ultimately, the choice of the appropriate capacity adjustment process depends on the objectives of the model, on the kind of business it belongs to and on the company's policies.

3.1.1 Balancing loop in the pipeline structure

Although feedback loops are not emphasized in the model's representation, there is a balancing loop between capacity and backlog at each stage, as seen in figure 4. When backlog goes up, available capacity also goes up due to the adjustment of capacity, and this increases the rate of projects that are reviewed (move to review); therefore, backlog is reduced.

Figure 4: Balancing loop




3.2 Attribute Creation Process

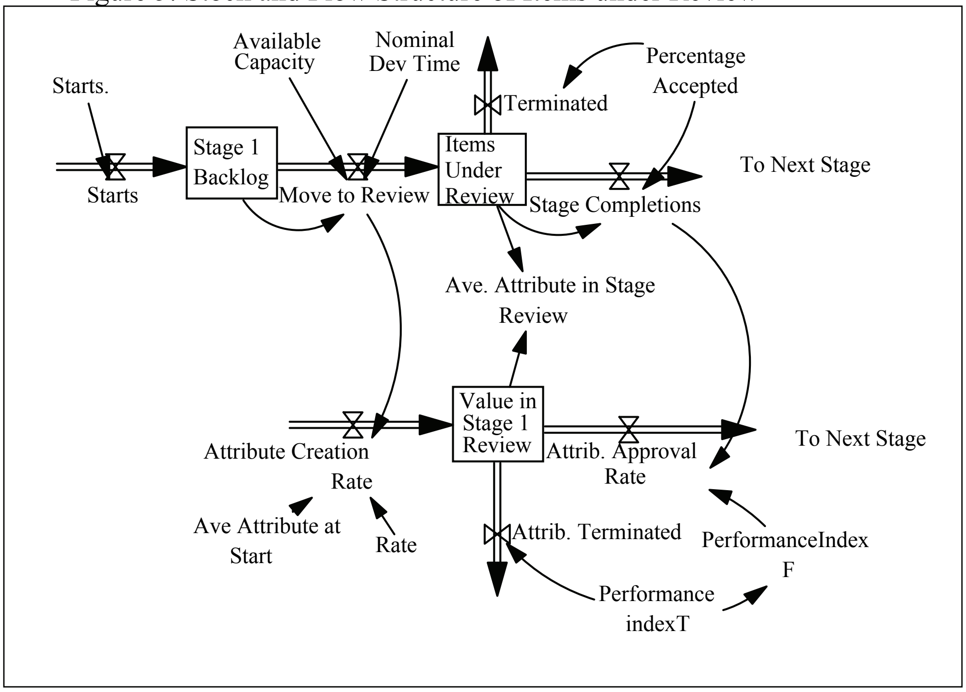
Managers are often endowed with limited resources. However, their focus is not limited to efficient resource allocation under these situations. They are also interested in the trade-offs between attribute value (a measure of performance or quality) and throughput involving aging chain decisions. This kind of trade-off was found in innovation settings (Wheelwright and Clark, 1992, pg. 91) and in the service industry. For instance, Oliva and Sterman (2001) identify "time per order" as a key construct that drives the service quality dynamics in a single stage model calibrated for a lending center at a UK bank. Capacity utilization was identified as a key construct that drives the performance of service supply chains (Anderson and Morrice 2005).

While it is clear that in the aforementioned cases attribute values are affected by how intensively employees are working, this may not be the case for other applications. Therefore, a simplification is made in which a constant rate for attribute creation is applied. Each attribute of each item is multiplied by the same constant (Rate) as it travels to the stock of attribute in review (see figure 5).

The available capacity derived from equations 1 and 2 is used within each stage during the process of attribute creation. A certain number of items enters stage 1 backlog. The co-flow stocks track the attributes of items along with their number. The average attribute of items is normalized to unity at start. This value is subsequently multiplied by a fixed factor (a

"Rate" value larger than 1) as items that were in the backlog are developed and go to the next phase to be reviewed (see equation 3). The "move to review" rate is equal to available capacity unless there is overcapacity (see equation 4). The items then reach the stock of "Items Under review". In this phase items are reviewed, and depending on the average attribute value (see section 3.4 for details), some fraction will be terminated and the rest will "follow the flow" to the next stage, the backlog of stage 2.

Figure 5: Stock and Flow Structure of Items under Review




$$\text{Attribute Creation Rate} = \text{Average Attribute at Start} * (\text{Rate}) * \text{Move to Review} \quad (3)$$

$$\text{Move to Review} = \text{MIN}\left(\frac{\text{Stage Backlog}}{\text{Nominal Dev Time}}, \text{Available Capacity}\right) \quad (4)$$

The rates of change in the stocks of stage backlog (stage in review and attribute in stage review) are calculated depending on the inflows and outflows to these stocks. Items that are approved in the second phase are launched or completed. The values of total attribute created, average attribute and number of items are tracked and used as performance measures.

Performance indices, T and F (on figure 6 above) are defined in the next section.

3.3 Project Screening Process

In order to screen items in a stock based on a specific attribute, it is necessary to know or assume the shape of the probability distribution function (PDF) of the population of attributes. Once this distribution is known, it is possible to determine the fraction of items that will be approved or terminated in each period based on the average attribute at each period, the pre-determined threshold (or minimum value) for such attribute and the standard deviation of the population.

In an aging chain with a co-flow, the average attribute of projects feeds into the screening process: the decision to proceed or terminate a fraction of items is made depending on the average value and a pre-determined threshold. The population of attributes of items after a review is assumed to follow a Gumbel distribution because screening is a search process that selects extreme values (Gumbel 1958, Galambos 1978, Dahan and Mendelson 2001). The Gumbel distribution is the probability distribution for multiple draws from exponential-tailed distributions. It applies to NPD problems especially well when there are no specific limits on the potential value of a project, but these values usually lie within a central range (Dahan and Mendelson 2001). The aforementioned authors also discuss the application of two other extreme value distributions; the Frechet distribution is particularly indicated to populations in which there is high upside uncertainty and items can become "mega-hits", yielding a very high attribute or performance. The Weibull distribution is indicated when there is an upper bound for the potential value of the attribute.

At any point in time, the population of attributes in a stock is distributed according to the extreme value Gumbel function, characterized by the mean attribute in the population and the corresponding standard deviation (see section 3.4). Even though a "maximum value" Gumbel distribution was used here (since items with higher attributes are selected), a "minimum value" distribution would have to be used in case the process involves screening and selecting items whose values fall *below* a pre-determined threshold. In such case, equation 5 would change.

The next section provides a summary of the Gumbel distribution and the formulation of percentage terminated/ accepted, Performance IndexT and Performance IndexF. The latter two are the corrections to the changes in value stocks based on percentage accepted, as shown in figure 6 above.

### 3.4 Screening using a Gumbel Distribution

The number of projects terminated or approved, depending on the net present value, is calculated by assuming that the values follow a Gumbel probability distribution, with a mean equal to "average value in stage review" and a selected standard deviation in stage 1 and in stage 2.

The choice of the standard deviation of the population of attributes at each stage can be made in many different ways, depending on the data available or on managerial choices. The simplest formulation is a constant value. However, standard deviations could also be chosen endogenously as a *fraction of the average attribute* at each stage. This would mean that populations of items with higher mean attributes will have proportionally larger variations. This assumption will be more or less appropriate depending on the process being modeled. For instance, it is reasonable to assume that managers in a product development pipeline attempt to *balance* the portfolio by introducing projects that cover a wider range of risks in terms of the attribute net present value (NPV). This is part of the strategy of many firms once it may not be adequate to have an entire population of projects with very high or very low risk (Cooper et al, 1998). The appropriateness of an endogenous variance, proportional to the mean NPV, will ultimately depend on the data from previous periods and on forecasting. In the case of human resources training pipeline, it is necessary to determine how the firm's hiring efforts are successful in introducing talents that consistently meet expectations in terms of qualification and performance. If the process is successful, employees will have less variance in qualification and performance (the attribute), and even a fixed value for attribute variation might be appropriate.

In case there is a known dynamic or seasonal effect on the variance of the population of attributes (so that variance changes over time), it is possible to use a time series for the variable. Alternatively, a more detailed formulation could be adopted with an agent-based simulation where there is full tractability of the individual items in the chain. We leave these options for follow on studies.

We establish the total attribute that is lost by screening and the total attribute that is transferred to the next stage by calculating the average attribute of the terminated items and the average attribute of the approved items. The same process is repeated for the second stage.

The probability density function of the Gumbel (maximum) distribution, which describes the relative likelihood for an item to occur at a given attribute value (x), is

$$f(x) = \frac{1}{\beta} e^{-\frac{(x-\mu)}{\beta}} e^{-e^{-\frac{(x-\mu)}{\beta}}} \quad (5)$$

Here μ is the location and β is the scale parameter. The mean is equal to μ + 0.5772β and the standard deviation is equal to 1.2825β. These two formulas are characteristic of the Gumbel distribution and are valid for any configuration of such distribution. Since μ is calculated every period and the standard deviation is pre-determined as a proportion of the mean attribute or as a time series, these parameters can be easily calculated. Therefore, we implement the calculation of termination criteria (P, or fraction of terminated items) using a table function computed from the following integral:

$$\text{Termination Criteria} = \int_{-\infty}^{Y} f(x)\,dx \quad (6)$$

The table function returns the fraction of terminated projects, for any “average value” on the X axis. The integration can be performed using MS excel. Percentage Accepted is the percentage complement of Termination Criteria.

If Y is the termination threshold, then the equation for setting up a table function for correcting the Average value of the terminated items is:

$$\text{Performanc e IndexT} = \frac{1}{P} \int_{-\infty}^{Y} x * f(x)\,dx \quad (7)$$

The table function returns the integral of equation 7 for each “average attribute” on the X axis. These values are then multiplied by 1/P in order to calculate the average value of terminated projects. The integration can be performed using MS excel.

In order to implement the screening process at each stage, a series of table functions had to be created, for each stage, for each pre-determined value of thresholds (see section 3.3 for details). For instance, if only one value of threshold is going to be used for each stage, it will be necessary to create two table functions for the first stage and two table functions for the second stage. Each couple of table functions calculates Performance IndexT and Termination Criteria. Additional pairs of table functions have to be created if other configurations of thresholds or standard deviations are going to be used, or if there are more stages in the pipeline.

The equation that calculates the index for average attribute of the approved items is:

$$\text{Performance IndexF} = \frac{\text{Ave Attribute in Stage Review} - \text{Performance IndexT} * (1 - \text{Percentage Accepted})}{\text{Percentage Accepted}} \quad (8)$$

The intuition for the above equation is that the average attribute of the entire population of items is equal to the weighted average of the average attributes of the terminated and approved items.

The number of items terminated is the number of items under review divided by the review time and multiplied by the percentage of terminated items. The calculation of the number of completions follows the same method. The attributes of items terminated is the number of terminated items multiplied by the performance index T (average attribute of terminated items). The calculation for attribute approval rate follows the same method.

**4. Discussion**

This study presents a new structure to system dynamics models of aging chains with co-flows. Such structure accounts for a specific phenomenon  the screening of items from stocks in the chain. This essential process has many possible applications as shown in the introductory section. We hope the model presented here will serve as a basis for studies in those areas, generating insights for practitioners and scholars.

The manner in which our model has been set up differs from inventory/ service supply chain models (Sterman 1989, Anderson and Morrice 2005) both in terms of stock/flow and policy structures. The key structural difference is that inventory and service supply chain models do not usually have exit flows (aka screens).

Ours is a highly stylized model that comes with several limitations. For instance, attribute creation rates and other variables were arbitrarily chosen; the model was not calibrated to a real company. This was a deliberate decision because a more generic version of the model can be more useful for other applications. We also do not account for dependencies among items, such as sharing of resources and sub-additive pay-offs (Girotra *et al*. 2005). Another simplification of this formulation is that the number of employees is fixed; therefore, an increase in capacity is automatically translated into an increase in utilization.

The limitation of managers' ability to account for the supply line and backlogs has been documented extensively in the inventory/services management context (Sterman 1989, Anderson and Morrice 2005). A related avenue for research, within the product innovation context, is to generate policy guidelines about the dynamics of capacity, resource utilization and backlog management while accounting for behavioral biases related to product innovation (Schmidt and Calantone 2002, Gino and Pisano 2005). Developing formal models of the economics of screening, in the presence of complexity and resource tradeoffs, either at a single stage or in a cascade of stages, and accounting for behavior bias (Gino and Pisano, 2005) offers opportunities for follow on work.

This study focuses on presenting a new structure to aging chains  enabling the process of screening. It could serve as a template for many other applications. These dynamic businesses and social processes, in which screening is present, represent huge investments by firms and the value of human lives. A deeper understanding of such processes, from simulation-based insights, could help improve public and private policies. Table 1 presents some of these possible applications; however, there certainly are many others, which constitute modeling opportunities.

The results presented here are meant to be descriptive in their nature. Since the objective of the model is to describe a basic common structure to the screening process, its decision or independent variables were not endogenized. The development of a model based on longitudinal data and additional behavioral information would allow some of these variables to be endogenous. For example, it is reasonable to assume that in product pipeline management, managers take into account capacity utilization when deciding on the number of projects to be started. Such additions to the model could be explored on follow-on studies.

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