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SCREENING ITEMS IN AN AGING CHAIN WITH A CO-FLOW STRUCTURE: AN APPLICATION TO THE PRODUCT PIPELINE MANAGEMENT PROBLEM

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ABSTRACT

In many situations, System Dynamics modelers have to capture attributes of items that are tracked in an aging chain. The outflow of items from the stocks in these chains usually depends on the attributes that are tracked in the co-flow. But 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. Many possible applications are suggested. An application to product pipeline management is developed.

Keywords: Screening; Co-flow; Extreme-value distribution; Gumbel distribution; Aging chains; Product development pipeline; Product development; Development funnel; System dynamics; Product portfolio management.

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 stock where 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.

Table 1 presents a list of possible applications for the screening process. 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, 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.

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. 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.

There are some key defining characteristics to most (but not all) processes involving 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 characteristic 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 (measured as Net Present Value, the attribute in the pipeline) 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 et al. 2005). Capacity utilization has been identified as a key construct that drives the performance of aging chains (Sundaramoorthy et al. 2012; Anderson and Morrice 2005).

Figure 1 presents a configuration adapted to the product pipeline management (PPM) process. 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 projects and of the stock of value shall have to be terminated, it is necessary to know which percentage of projects has a value lower than the pre-determined threshold. While calculating such percentage, assumptions have to be made on how the population of NPVs of projects is distributed, i.e. what the probability distribution function (PDF) of the NPVs 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 (PPM)h	Projects	Net Present Value (NPV)	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

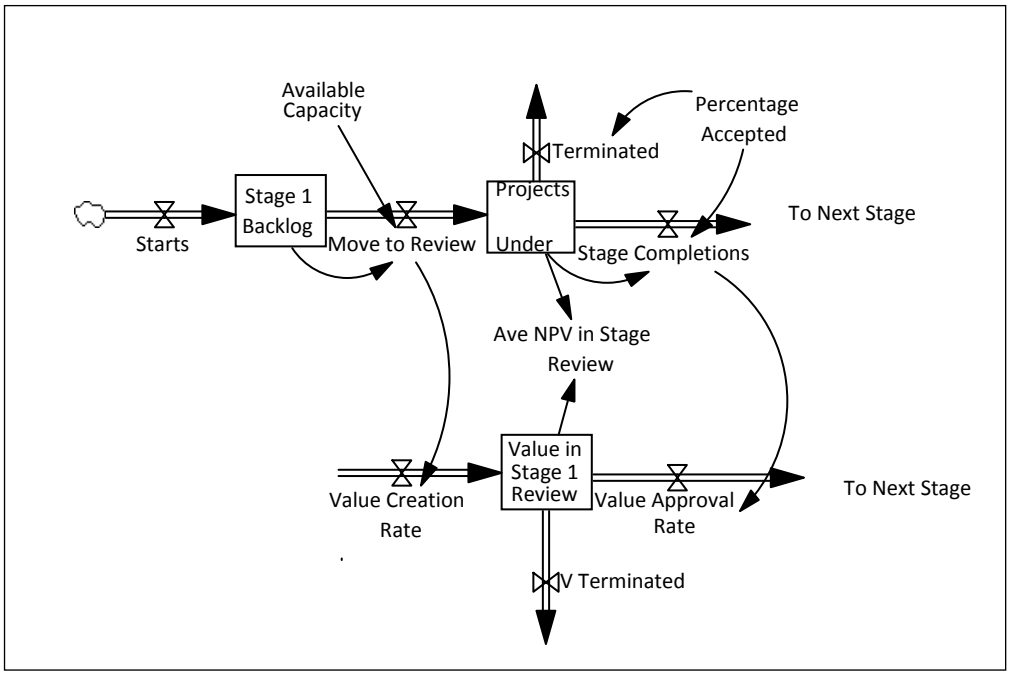
*How the attribute in the co-flow changes from one stage to the next. "+" means positive change. "–" means negative.

** See section 3.4. 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

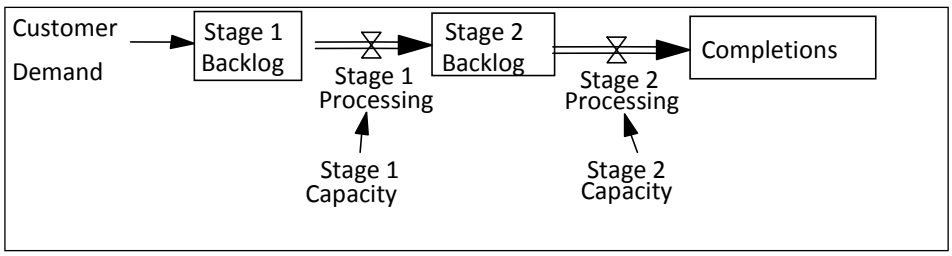
Figure 1: Single stage coflow with screening (simplified)



1.1 Model Use

The model developed here represents product pipeline management (PPM) decision-making. The term product pipeline management alludes to the practice of starting and steering several new product development (NPD) projects through a sequence of screens. The structure of stocks and flows in PPM can be compared to the structure of a service supply chain model (Anderson *et al*. 2005) as shown in figure 2. The PPM problem is a special case of service supply chains where some projects are terminated across stages based on their value.

Figure 2: A Service supply chain (Anderson *et al*. 2005)



The objective of the model presented here is to describe a basic common structure to the screening process. This version was created to make the model as generic as possible, and applicable to many different processes and settings; a more complex version of the model can be found in

Figueiredo and Loiola (2012). Such version adds two variables that were initially treated as constants: the allocation of resources across stages (manhours per month at each stage) and the complexity of projects (manhours per project at each stage). Figueiredo and Loiola (2012) aimed to show proof that the model formulations generate the appropriate response and the stock population has the desired characteristics, by showing simulation results and a detailed explanation on how the formulations preserve these characteristics. The paper focuses on validation and optimization. Data from the Novartis innovation chain were used, and the calibrated model achieved a goodness of fit of ±5%. Such study, however, did not document the model, i.e. neither the equations were presented nor was the screening process explained in detail. The present study aims to fill this void.

2. RESEARCH SETUP

We steer away from analyzing phase-gate processes that do not screen out products, and instead focus on the funnels, and especially their fuzzy (uncertain) front ends (Khurana and Rosenthal, 1997; Jugend and Silva, 2012), where products have to go through fundamentally different kinds of assessments across a succession of screens that determinate the shape of the innovation funnel (Krishnan and Ulrich 2001; Terwiesch and Ulrich 2009).

An established body of literature characterizes product pipeline decisions as a dynamic problem that is often beset with congestion effects (Laínez et al. 2012; Griffin 1997; Ulrich and Eppinger 2004). For example, Adler *et al.* (1995) modeled the project development organization by setting engineering resources as "workstations" and projects as "jobs" that flow between the workstations. At any one stage of the pipeline, PPM decisions can be studied as a portfolio management problem. For instance, Banerjee and Hopp (2001) and Chao et al. (2009) studied how limited resources must be allocated among a set of candidate projects over time. Building on the Banerjee and Hopp formulation, Gino and Pisano (2005) have taken a behavioral approach to this problem and explored the application of such policies to test heuristics for resource allocation across multiple stages of a pharmaceutical R&D process. Other papers focus on optimization of the portfolio management problem (Smith and Ierapepritou 2011), on optimizing clinical trial supply chain management (Chen et al. 2012) and on optimization of resource planning and scheduling of tasks in PPM (Colvin and Maravelias 2011). Some empirical studies have explored the patterns, best practices or benchmarks in the managerial decisions concerning PPM (Schmidt et al., 2008; Rusu et al., 2011; Hurtado, 2009).

3. MODEL DESCRIPTION

Most firms use multiple, typically four to six, gates in their pipelines (Perez-Escobedo et al., 2012; Ulrich and Eppinger 2004). For parsimony, our model incorporates only two gates. Outcome variables of interest are the total value created, and the average value created at the end of the pipeline. The independent variables in our model are number of projects introduced into the pipeline, minimum acceptable value in each stage (thresholds 1 and 2), and the managerial biases in adjusting capacity. The model structure can be divided in three basic processes: capacity management, screening and value creation. These are described next.

3.1 Capacity Management Process

A central construct of the model is the utilization of capacity. This construct is present not only in product development pipelines, but also in a number of other applications (see table 1). 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 PPM settings, changes in capacity utilization have been shown to affect attribute performance. In many 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, which enhances the level of attributes at each stage. This is exemplified in section 3.2.1.

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 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 value 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 (here called "Nominal Capacity").

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).

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

Change in Capacity is modeled as a first order exponential adjustment of Available 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 value) and the demanded rate of development in each gate based on the backlog.

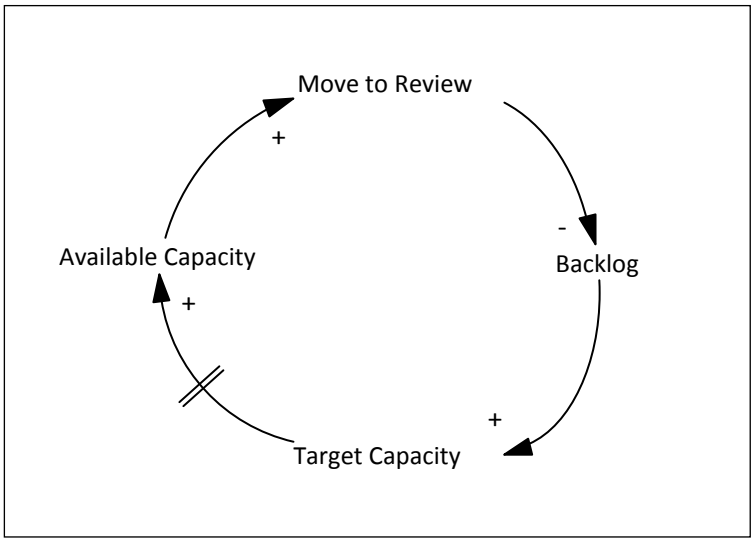
$$\text{Target Capacity} = \frac{\alpha * \text{Stage Backlog}}{\text{Nominal Dev Time}} + (1-\alpha) * (2 - \text{Utilization}) * \text{Nominal Capacity} \quad (2)$$

Here α 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). 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 PPM model's representation, there is a balancing loop between capacity and backlog at each stage. When the 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 3: Balancing loop



3.2 Value Creation Process

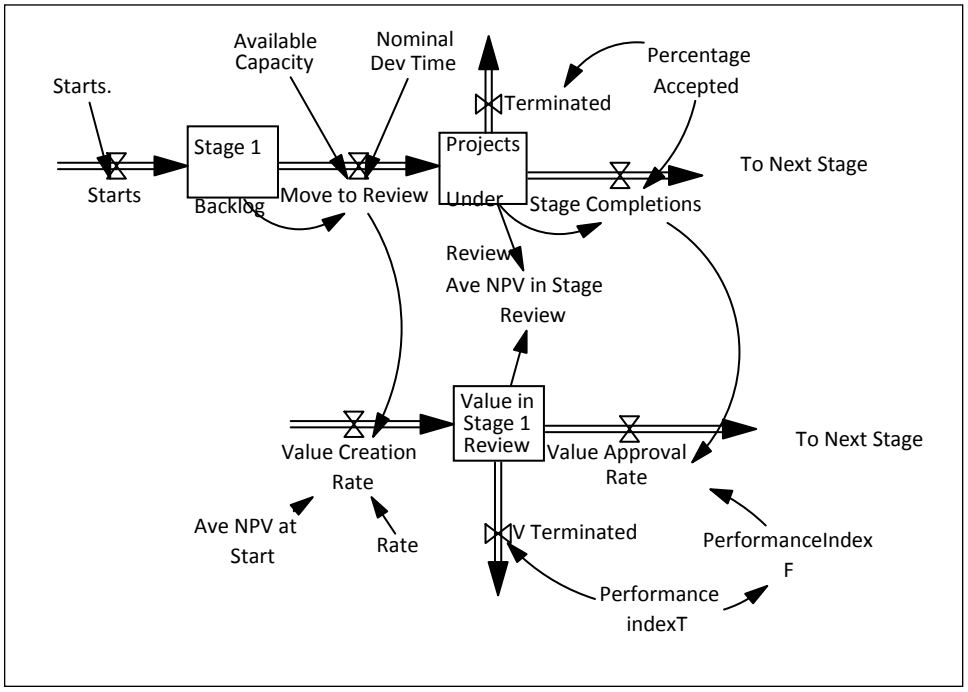
Managers are often endowed with limited resources. However, their focus is not limited to efficient resource allocation under these situations. They are also interested in the trade-offs between attribute value (a measure of performance or quality) and throughput involving aging chain decisions. This 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 value creation is applied. Each NPV of each project is multiplied by the same constant (Rate) as it travels to the stock of projects under review (see figure 4).

The available capacity derived from equations 1 and 2 is used within each stage during the process of value creation. A certain number of projects enters stage 1 backlog. The co-flow stocks track the NPVs of items along with their number. This value is subsequently multiplied by a fixed factor (a "Rate" value larger than 1) as projects 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 "Projects Under review". In this phase projects are reviewed, and depending on the average NPV (see section 3.3 for

details), some fraction will be terminated and the rest will "follow the flow" to the next stage, the backlog of stage 2.

Figure 4: Stock and Flow Structure of a Typical Gate (simplified)



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

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

The rates of change in the stocks of stage backlog, stage in review, and value in stage review are calculated depending on the inflows and outflows to these stocks. Projects that are approved in the second phase are launched to the market. The values of total value created and number of projects are tracked and used as performance measures.

Performance indices, T and F (on figure 4 above) are defined in section 3.3.

3.2.1 Variable value creation

While the design of the model was consistent with expectations, the simplifying assumption of constant value creation rates may not be realistic. A relevant assumption for product development pipelines is that the relationship between capacity utilization and value created in each gate, instead of

being constant, has an inverted U shape, with the peak value being observed at nominal value of utilization. This assumption follows field observations by Wheelwright and Clark (1992, pg. 91) and by Girotra *at al.* (2005). The former authors show how employee productivity (percent of time spent on *value-adding* tasks) initially increases and then decreases as the number of development projects assigned concurrently to each engineer increases. The latter authors have pointed out that total development costs can be thought of as the sum of opportunity costs and the cost of capacity, resulting in a convex function of capacity utilization. We capture this effect in a table function that establishes a concave relation between utilization and value created. The updated equation 3, which calculates value creation is:

$$Value\ Creation\ Rate = AverageNPV\ at\ Start * \big(1 + Adjustment(Utilization)\big) * MovetoReview \quad (3')$$

Adjustment is the table function that establishes the concave relation between value creation and utilization, as determined by Wheelwright and Clark (1992, pg. 91).

3.3 Project Screening Process

In order to screen items in a stock, based on the performance of these items in terms of a specific attribute, it is necessary to know or assume the shape of the probability distribution function (PDF) of the population of attributes. In an NPD pipeline, 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). In other words, the population of attributes of items that survives a review is assumed to follow a Gumbel distribution because screening is a multi-stage search process that selects extreme values. According to Dahan and Mendelson (2001, pages 108 and 109): "*when the maximum is taken over a large number of random variables, its asymptotic distribution is given by extreme value theory*……Since product ideas that are good enough to make into a "short list" are each a maximum from a large sample of subconcepts drawn from H(x), F(x) also takes the form of one of the three extreme –value distributions". Similarly, Terwiesch and Xu (2008) state that "problem solving in innovation is often stochastic, which we capture by adding a noise variable to the performance. Given this uncertain performance, the solver will most likely engage in a search process by conducting a set of *trials*. The results of an experiment are captured by the multiple realizations of the random variable. Following the work by Dahan and Mendelson (2001), we consider the specific case in which the random noise is an independent and identically-distributed Gumbel random variable." In another setting, Kosmrlj et al. (2009) map thymic selection processes to an extreme value problem and provide an analytic expression for the amino acid

compositions of selected T-cell receptors. The authors explain that Thymocytes expressing a T-cell receptor that binds with high affinity to any self-p major histocompatibility molecule are deleted in the thymus (a process called negative selection). However, a thymocyte's T-cell receptor must also bind sufficiently strongly to at least one self major histocompatibility protein complex to receive survival signals and emerge from the thymus (a process called positive selection). The authors supply a equation that casts thymic selection as an extreme value problem , enabling the calculation of the probability that a T-cell receptor sequence will be selected in the thymus."

The Gumbel 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 3.3.1).

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 4 above.

3.3.1 Screening using a Gumbel Distribution

The number of projects that are 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. 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, for example, as a *fraction of the average attribute* at each stage. The appropriateness of an endogenous variance, proportional to the mean NPV, or other formulations, will ultimately depend on problem being modeled, on the data from previous periods and on forecasting.

We establish the total value that is lost and the total value that is transferred to the next stage by calculating the average value of the terminated projects and the average value of the approved projects. 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 (project) to occur at a given attribute (x, or NPV), 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-defined, these parameters can easily be calculated. Therefore, we implement the calculation of termination criteria (P, or fraction of terminated projects) using a table function computed from the following integral:

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

The percentage accepted is percentage complement of the 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 projects is:

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

In order to implement the screening process at each stage, a series of table functions had to be created, for each stage, for each chosen standard deviation of values and for each pre-determined value of thresholds. 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 value of the approved projects is:

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

The intuition for the above equation is that the average NPV of the entire population of projects is equal to the weighted average of the average NPVs of the terminated and approved projects.

The number of projects terminated is the number of projects under review divided by the review time, and multiplied by the percentage of terminated projects. The calculation of the number of completions follows the same method. The value of projects terminated is the number of terminated projects multiplied by the performance index T (average value of terminated projects). The calculation for value 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, value 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 behavioral bias offers opportunities for follow on works.

This study could serve as a template for many other applications. The 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 are certainly 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. Figueiredo and Loiola (2012) are an example of a follow on study that validates the present model by calibrating it to a specific product development pipeline (The Novartis innovation chain) and showing that the results from the SD model using the proposed formulation are consistent with the results from the numerical example.

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SELECIONANDO ITENS NUMA CADEIA TEMPORAL COM ESTRUTURA DE FLUXO AUXILIAR: UMA APLICAÇÃO PARA A GESTÃO DO FUNIL DA INOVAÇÃO

RESUMO

Em muitas situações na modelagem de dinâmica de sistemas, é necessário capturar atributos de items que são rastreados numa cadeia temporal. A saída de itens destes estoques geralmente depende dos atributos que são rastreados em um fluxo auxiliar. Contudo, estes modelos clássicos não consideram um fenômeno específico, a seleção de itens. Este estudo apresenta uma nova aplicação para fluxos auxiliares em cadeias temporais: Um fluxo auxiliar que permite o processo de seleção, i.e. o processo de eliminar ou aprovar itens dependendo do valor de um atributo. São sugeridas muitas aplicações possíveis para a nova estrutura. Uma aplicação para a gestão do funil de inovação é desenvolvida.

Palavras-chave: Seleção; Fluxo auxiliar; Distribuição de probabilidade de valor extremo; Distribuição Gumbel; Cadeias temporais; Funil da inovação; Desenvolvimento de produtos; Gestão de portfolio de projetos; Dinâmica de sistemas.

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