Ernane Rosa Martins
(Organizador)

Pesquisa Operacional e sua Atuação Multidisciplinar

Atena Editora
Ano 2019

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Atena Editora
2019

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Editora Executiva: Profª Drª Antonella Carvalho de Oliveira
Diagramação: Karine de Lima
Edição de Arte: Lorena Prestes
Revisão: Os Autores

Dados Internacionais de Catalogação na Publicação (CIP)
(eDOC BRASIL, Belo Horizonte/MG)

P474 Pesquisa operacional e sua atuação multidisciplinar [recurso eletrônico] / Organizador Ernane Rosa Martins. – Ponta Grossa, PR: Atena Editora, 2019.

Formato: PDF
Requisitos de sistema: Adobe Acrobat Reader
Modo de acesso: World Wide Web
Inclui bibliografia
ISBN 978-85-7247-478-8
DOI 10.22533/at.ed.788191107

1. Pesquisa operacional. I. Martins, Ernane Rosa.
CDD 658.51

Elaborado por Maurício Amormino Júnior – CRB6/2422

Atena Editora
Ponta Grossa – Paraná - Brasil
www.atenaeditora.com.br
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Atena Editora
Ano 2019

APRESENTAÇÃO

A Pesquisa Operacional (PO) utiliza a matemática, a estatística e a computação para auxiliar na solução de problemas reais, com foco na tomada das melhores decisões nas mais diversas áreas científicas e de atuação humana, buscando otimizar e melhorar suas performances. Através do uso de técnicas de modelagem matemática e eficientes algoritmos computacionais, a PO vem cada vez mais atuando na análise dos mais variados aspectos e situações de problemas complexos em demandas de inúmeras áreas, principalmente por conta de sua flexibilidade de aplicação e interação multidisciplinar, permitindo a tomada de decisões efetivas e a construção de sistemas mais produtivos.

Esta obra reúne importantes trabalhos que envolvem o uso de PO, realizados em diversas instituições de ensino do Brasil, abordando assuntos atuais e relevantes, tais como: modelos matemáticos; otimização multiobjectivo; heurísticas; algoritmos; otimização geométrica; metodologia SODA; soft systems methodology; strategic choice approach; procedimentos metodológicos de análise estatística; jogos cooperativos; algoritmos genéticos; método VIKOR; regressão linear múltipla; algoritmos de aprendizado de máquina; análise de decisão multicritério e composição probabilística de preferências.

A importância desta coletânea está na excelência dos trabalhos apresentados e na contribuição dos seus autores em temos de experiências e vivências. A socialização destes estudos no meio acadêmico, permite ampla análise e inúmeras discussões sobre diversos assuntos pertinentes referentes a atuação multidisciplinar da PO. Por fim, agradeço a todos que contribuíram na construção desta belíssima obra e desejo a todos os leitores, boas reflexões sobre os assuntos abordados.

Ernane Rosa Martins

SUMÁRIO

CAPÍTULO 14

A STOCHASTIC DYNAMIC MODEL FOR SUPPORT OF THE MANAGEMENT OF NEW PRODUCT DEVELOPMENT PORTFOLIOS

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ABSTRACT: New Product Development Processes are, in general, costly for organizations and since they need to coordinate the allocation of resources through several projects of the innovation funnel, the management of product portfolio aiming the best expected return is an important challenge. In this context, the present study aims to develop a mathematical model capable of considering, in an integrated manner, the uncertainties and the dynamicity in portfolio management. Also, we propose two heuristic policies and use the developed model as a framework for their comparison through simulation.

KEYWORDS: New product development portfolios; Dynamic Programming; Heuristic Policies.

RESUMO: Processos de desenvolvimento de novos produtos são, em geral, custosos para as organizações e uma vez que estas necessitam de coordenar a alocação de recursos entre vários projetos dentro do funil de inovação, a gestão do portfólio de produtos objetivando o melhor retorno esperado é um importante desafio. Neste contexto, o presente trabalho tem como objetivo desenvolver um modelo matemático capaz de considerar, de forma integrada, as incertezas e a dinamicidade na gestão de portfólios. Ademais, propusemos também duas políticas heurísticas e utilizamos o modelo como um framework para comparação através de simulação.

PALAVRAS-CHAVE: Portfólio de desenvolvimento de novos produtos; Programação Dinâmica; Heurísticas.

1 I INTRODUCTION

The competition in the market of consumer goods is characterized by the constant introduction of new products, as well as the substitution or the enhancement of the already existent products. This characteristic, together with the dynamicity and the uncertainties of these markets, exposes the importance of the efficient management of available resources for Research and Development (R&D) inside of competing businesses.

Furthermore, as pointed by Bromiley et al. (2017), the difficulty of companies to manage their own product portfolio becomes significant due to the multiple projects and the several sources of uncertainties associated with them. In this context, it is necessary to search for methods that help the management of developing portfolios considering, in an integrated way, the deployment of each product regarding the uncertainties and the dynamicity of the whole system.

The new products portfolio management problem is recurrent in literature and, in general, the focus is the creation of decision tools able to consider the expected return of the projects and, in some cases (e.g. Loch e Kavadias (2002); Stummer e Heidenberger (2003); Li et al. (2016)), the dependency of this return on the existence of other projects and or market products. An important constraint is the limit of resources, both non-renewable and renewable ones.

Even when the approaches consider the same constraints, the decisions made might differ between studies. Soares Figueiredo e Loiola (2012) and Figueiredo e Loiola (2017) focus on the number of projects to be developed each step of the innovation funnel, which culminates into the decision to discontinue or not a project. However, in most of the studies, the main decision is related to the allocation of resources to each project (e.g. Loch e Kavadias (2002); Stummer e Heidenberger (2003); Carazo et al. (2010); Li et al. (2015, 2016)).

In a more operational perspective, some studies treat the initial date of development (e.g. Li et al. (2015, 2016); Tian et al. (2016)) or the sequence of the development of projects (e.g. Carazo et al. (2010); Tian et al. (2016)).

Li et al. (2015) and Li et al. (2016) and Tian et al. (2016) consider the possibility of preemption (freezing) of developing projects through the temporary non allocation of resources for the frozen project. The freezing strategy justifies itself due to the value of the flexibility generated by the environmental changes that may occur after the realization of uncertainties.

The models referred in literature could be classified as dynamic or stochastic. An optimization model is said to be dynamic when the decision making considers that, in the future, the decision scenario will be reevaluated in an optimal way due to new generated conditions by the realization of uncertainties. Within the studies cited, only Loch e Kavadias (2002), Figueiredo e Loiola (2012) and Figueiredo e Loiola (2017) approach the question in a dynamic manner.

Within the related context, this study has as it's objective to develop a mathematical model based on stochastic dynamic programming capable of aiding the decision making in the management of the portfolio of new products. The presented model in this study differentiates from other stochastic models found in literature for approaching the problem in a dynamic way, and differentiates itself from Loch e Kavadias (2002), Figueiredo e Loiola (2012) and Figueiredo e Loiola (2017) for considering more operational decisions about the projects in an integrated form.

In this way, the main contribution of the current study is the development of a mathematical model able to consider uncertainties and the dynamicity within the portfolio management in an integrated way with the operational decisions of each project, supplying a framework for comparing policies that may be used for the construction of optimal policies in future studies.

As a secondary contribution, this study presents and compares two alternative policies for the problem through computational tests.

After this introductory section, the description of the problem and the proposed mathematical modeling are presented in Section 2. In Section 3, two heuristic policies are described and your performances compared via simulation in Section 4. Lastly, Section 5 exposes the final consideration and indicates the future trail of the research.

2 I DESCRIPTION AND MATHEMATICAL MODELING

Rozenfeld et al. (2006) points out that the use of the concepts of Development funnel, or Innovation funnel, brings benefits when working with the simultaneous PDP. First, there are a large number of ideas that are selected - through stages of managerial decisions - in a smaller number of product designs which, in turn, result in even fewer numbers for parallel development. Finally, only a few products are released on the market. Figure 1 shows this process by illustrating an innovation funnel and explains the different market requirements.

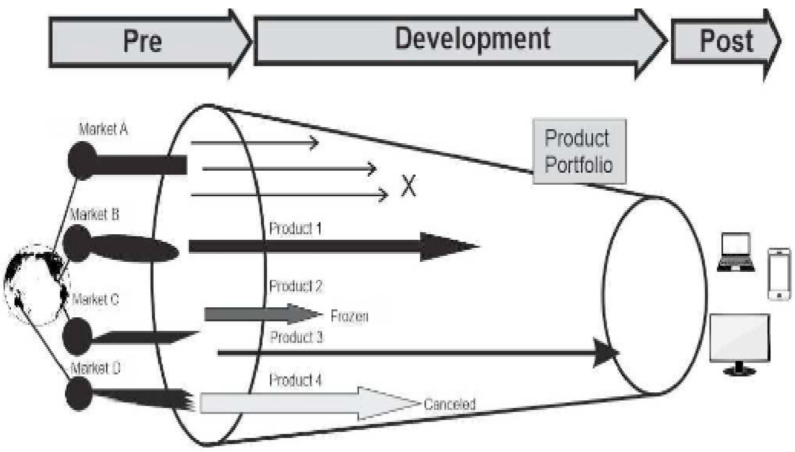


Figure 1: Development funnel

Source: Adapted from Rozenfeld et al. [2006].

In this study, the development portfolio will be represented by a P set of projects that are being developed. Once projects are embedded in the innovation funnel, the portfolio is segmented through a E set of steps, the elements of which represent the steps of the Innovation funnel. In this way, the subsets $P_e \subseteq P$ contain the projects under development that are in step $e \in E$ of the Innovation funnel.

The project portfolio P can also be partitioned by the company's development focus areas (set A), being $P_a \subseteq P$ the set of projects that belong to the area $a \in A$ of the company. Finally, we can define $P_l \subseteq P$ as the projects that can be released to the market.

The model presented in this work has a dynamic character, since it is re-evaluated continuously, that is to say, in a certain period of time the aspects that compose it will be revised in order to reach the main objective, that is to maximize the return of the portfolio of product projects to be launched.

2.1 System State And Decision Stage

A stage is an instant of time when a decision is made in the system and is represented by $t \in$ N. The problem was modeled considering the horizon of infinite planning, in other words, by having infinite stages of decision. A period represents the interval between two consecutive stages. In this paper, the unit chosen for the period represents the time interval in which the company reviews its portfolio.

The proposed model has a dynamic character since it reassesses itself in a continuous way and in each stage of decision, the aspects that form it, seeking to reach the maximization of the return of the portfolio of product projects to be launched.

The review of the decision at each stage is necessary due to the presence of uncertainties that are inherent in the system, such as the expected return value of the project at its launch, the level of market demand or the residual time required to complete the development project.

The state is defined as a cluster of information needed to describe and evaluate the system at the time of decision making. In this study we will represent the system state in the stage $t \in N$ as $S^{(t)}$, containing the following parameters:

- Funnel: the sets $P^{(t)}$; $P_e^{(t)}, \forall e \in E$; $P_a^{(t)}, \forall a \in A$ e $P_l^{(t)}$ combine and characterize all projects that are in the innovation funnel;
- Budget: this parameter $or^{(t)}$ expresses the amount of total resource invested by the company;
- Characteristics of each project $p \in P^{(t)}$: projects are also part of the state, so their characteristics must be considered. There are the cost of each project $c^{(t)}_{e,m,p}$ the expected return function of each project F_p^t, which in turn, depends on the expected performance of each project at the end of development $d^{(t)}_p$ and the number of periods required to move to the next step $\tau_{(t)}$. In addition to those mentioned, the projects also have as parameters the indicator that

it may or may not be divided (frozen) $div_p^{(t)}$. The freezing time limit is given by $cgmax_p$ and the cumulative freezing time is represented by $cgt_p^{(t)}$.

Thus, it is possible to represent the state of the system through the expression 1:

$$S^{(t)} = \left(P^{(t)} = \bigcup_{e \in E} P_e^{(t)} = \bigcup_{a \in A} P_a^{(t)},\ P_l^{(t)}, or^{(t)} \right) \qquad (1)$$

2.2 Uncertainties

The return generated by a project is uncertain because its value is dependent on random parameters that are exogenous and endogenous to the process of product development. Following the line of Huchzermeier e Loch (2001), this model incorporates five sources of uncertainty:

1. Resources: associated with the material and human resources initially established. It is modeled by varying the value needed to execute a project along the development ($c^{(t)}_{e,m,p}$);

2. Performance: that a product achieves at the end of its development. It is modeled by updating the expected performance of the project at launch time $d^{(t)}_{p}$;

3. Schedule: related to the forecast of the product launch in the market due to the occurrence of delays during the development. Updating the τ^e parameter models the time required for the project $p \in P_e$ to complete step $e \in E$;

4. Market requirements: tied to the level of consumer demand for product performance. This uncertainty is modeled in this study as being a random variable Rp, with a presumed known distribution;

5. Market return: exogenous uncertainty that depends on decisions of factors intrinsic to market agents, such as consumers and other competitors. Determines the amount billed by a project given its performance, the time of its launch and the market requirements. This uncertainty is characterized by parameterizing the return function $F^{(t)}_p(d_p, \tau_p^l, R_p)$ *for the* $p \in$ P at the time of it's launch (τ_p^l).

In addition to the uncertainties present in Huchzermeier e Loch (2001), the developed model also contains the uncertainty regarding the arrival of a new project in the first stage of the funnel. This arrival is represented by a stochastic process.

2.3 Decision

If S is a possible state of occurrence, $u = \pi(S)$ is a viable decision determined by controlling the system with the π, ω the policy with the sources of uncertainty present in the system, S' a possible state to occur from the transition generated by S, u and ω (discussed in subsection 2.4), γ the discount factor, $F^{\pi}(S, u)$ the immediate return received by applying π to S, the equation 2 is known as the Bellman equation for the fixed policy π and determines the value V^{π} of being in S.

$$V^{\pi}(S) = G\big(S, \pi(S)\big) + \gamma E_{\omega}\{V^{\pi}(S')|S, \pi(S)\} \quad (2)$$

The objective of the problem is to find the optimal policy π^* that maximizes the value V^{π}, as expressed by the Equation 3. The Equation 4 is known as Bellman's Optimality Equation, which, according to Powell (2007), proposes the resolution of dynamic problems in a way that takes into account the probability of a certain action being taken and, consequently, the return of this action and the values it will assume. The set U is the set of viable actions for the system when it is in S.

$$\pi^* = argmax_{\pi \in \Pi} V\, \pi(S) \quad (3)$$

$$V^{\pi^*}(S) = max_{u \in U}\left\{ G\big(S, u = \pi^*(S)\big) + \gamma E_{\omega}\left[V^{\pi^*}(S') \middle| S, u = \pi^*(S)\right]\right\} \quad (4)$$

Specifically in this problem, $G(S, u)$ represents the expected total return $R(Pl)$ of projects that can be posted in S ($p \in Pl$) decreasing from costs of projects selected for execution $C^d(S, u)$ and the costs associated with the constraint violations *soft* ($Cv^a(S, u)$ e $Cv^e(S, u)$). Equation 5 details the composition of $G(S, u)$ at a given decision stage t.

$$G_t\big(S^{(t)}, u^{(t)}\big) = R_t\big(Pl^{(t)}\big) - C_t^d\big(S^{(t)}, u^{(t)}\big) - Cv_t^a\big(S^{(t)}, u_{(t)}\big) - Cv_t^e\big(S^{(t)}, u^{(t)}\big) \quad (5)$$

The decision $u^{(t)}$ taken at a given stage of the system encompasses the allocation of resources at each stage, in each area and in each project. For each step $e \in E$ of the funnel is defined as a continuous variable $tn_e^{(t)}$ which represents the total resource allocated to the project that are in this step.

Individually, the allocation of resources in a given project can determine its execution mode, its cancellation or even its freezing, when preemption is a possibility.

The execution modes of a project ($m \in M_{e,p}, \forall e \in E, \forall p \in P$) are step-dependent and determine the probability of success in execution in the next period, the expectation of performance variation, the probability of delay, the variation in the residual development time in case of success and the execution cost for the next period ($c_{e,m,p}$). Note that once the system stage (t) is instantiated, each project will be in a certain step $e \in E$ and therefore it will be possible to refer to the set of execution modes based on the project only p , of the stage $M_p^{(t)}$ and of costs $c^{(t)}_{m,p}$.

For each project p is defined a binary variable $y_p^{(t)}$ that indicates cancellation; if $p \in Pc$, a binary variable $f_p^{(t)}$ indicating it's freezing; and for each mode $m \in M_p^{(t)}$, a binary variable $w^{(t)}_{m.p}$ which indicates the execution of the project p with the m mode.

Accordingly, $r_{m,p}^{(t)}$ being a parameter that indicates the return, in terms of present value obtained after executing the last phase of the last step (launch) of a project $p \in P_l^{(t)}$ through the mode $m \in M_p^{(t)}$, $R_t(P_l^{(t)})$ is defined by Equation 6. $C_t^d(S^{(t)}, u^{(t)})$ is defined by equation 7, $Cv_t^a(S^{(t)}, u^{(t)})$ by Equation 8 and $Cv_t^e(S^{(t)}, u^{(t)})$ by equation 9.

$$R_t\left(P_l^{(t)}\right) = \sum_{p \in p_l^{(t)}} \sum_{m \in M_p^{(t)}} r_{m,p}^{(t)} * w_{m,p}^{(t)} \quad (6)$$

$$C_t^d\left(S^{(t)}, u^{(t)}\right) = \sum_{e \in E} tn_e^{(t)} \quad (7)$$

$$Cv_t^a\left(S^{(t)}, u^{(t)}\right) = \sum_{e \in A} \rho_1 * L_a^{(t)} \quad (8)$$

$$Cv_t^e\left(S^{(t)}, u^{(t)}\right) = \sum_{e \in E} \sum_{p \in \mathrm{P}_e^{(t)}} \rho_2 * J_{e,p}^{(t)} \quad (9)$$

In Equation 8, $L_a^{(t)}$, $\forall a \in A$ is a binary variable that indicates the constraint (15) violation representing the minimum budget share allocated to area $a \in A$ of the company. In the same sense, in Equation 9, $J_{e,p}^{(t)}$ is a binary variable that indicates the restriction violation (14), representing the maximum limit of resources allocated to the same project $p \in P_e$ for each step of the funnel. The parameters ρ_1 and ρ_2 are penalty constants for violations in the area and design constraints per step, respectively.

Given this, for the problem presented in this study, the equation 4 can be rewritten as shown in Equation 10.

$$Obj: V\left(S^{(t)}\right) = max_{u \in U^{(t)}} \{ \sum_{p \in P_l^{(t)}} \sum_{m \in M_p^{(t)}} r_{m.p}^{(t)} * w_{m,p}^{(t)} - \sum_{e \in E} tn_e^{(t)} - \sum_{a \in A} \rho_1 * L_a^{(t)} - \sum_{e \in E} \sum_{p \in P_e^{(t)}} \rho_2 * J_{e,p}^{(t)} + \gamma E_\omega\left[V\left(S^{(t+1)} \middle| S^{(t)}, u\right]\right\} \quad (10)$$

Subject to the constraint set expressed by $U^{(t)}$, such that:

$$y_p^{(t)} + \sum_{m \in M_p^{(t)}} w_{m,p}^{(t)} = 1, \qquad \forall p \in P^{(t)} \setminus \{P_c^{(t)}\} \quad (11)$$

$$y_p^{(t)} + f_p^{(t)} + \sum_{m \in M_p^{(t)}} w_{m,p}^{(t)} = 1, \qquad \forall p \in P_c^{(t)} \quad (12)$$

$$\sum_{m \in M_p^{(t)}} \sum_{p \in P_e^{(t)}} w_{m,p}^{(t)} * c_{m,p}^{(t)} = tn_e^{(t)}, \qquad \forall e \in E \ (13)$$

$$\sum_{m \in M_p^{(t)}} w_{m,p}^{(t)} * c_{m,p}^{(t)} \leq \varphi * tn_e^{(t)} + J_{e,p}^{(t)} * or^{(t)}, \qquad \forall e \in E, \forall p \in P_e^{(t)} (14)$$

$$\sum_{m \in M_p^{(t)}} \sum_{p \in P_a^{(t)}} w_{m,p}^{(t)} * c_{m,p}^{(t)} \geq Quota_a^{(t)} - L_a^{(t)} * or^{(t)}, \qquad \forall a \in A \ (15)$$

$$Quota_a^{(t)} \geq \sum_{e \in E} \beta * tn_e^{(t)} - or^{(t)} * \left(1 - mn_a^{(t)}\right), \qquad \forall a \in A \ (16)$$

$$Quota_a^{(t)} \geq \sum_{p \in P_a^{(t)}} cmin_p^{(t)} - 2 * cmin_p^{(t)} * \left(mn_a^{(t)}\right), \qquad \forall a \in A \ (17)$$

$$\sum_{e \in E} tn_e^{(t)} \leq or^{(t)} \qquad (18)$$

The constraints 11 and 12 relate to the project status *p*. While the constraint 12 ensures that a project can be active - in a certain way $m \in M_p^{(t)}$ – abandoned – expressed by the binary variable $y_p^{(t)}$ - or frozen - expressed by the binary variable $y_p^{(t)}$, for all projects that are included in the set $Pc^{(t)}$, the constraint 11 imposes the same condition, however in the set $P^{(t)}$ excluding $Pc^{(t)}$. Therefore, it is applied to all projects under development, except for those that can be frozen.

The constraint 13 determines the resource allocation per funnel stage. The sum of the execution costs $c^{(t)}_{m,p}$ relative to the project execution mode *p* active in $w^{(t)}_{m,p}$ must be equal to quantity of allocated resources $tn_e^{(t)}$ in a certain step of the funnel $e \in E$.

There should also be restrictions that control the amount allocated, in percentage, of resources in the projects, individually, per funnel stage. Thus, constraint 14 limits the resource allocated to a single project to be $\phi * tn_e^{(t)}$, where $\phi \in [0, 1]$ is a predetermined constant. Because it is a soft constraint, it can be relaxed by associating the value with the variable $J_{e,p}^{(t)}$, making the constraint redundant.

The constraints 15 - 17 are associated with balancing by project area along the funnel. Restriction 15 guarantees a minimum quota to be allocated to projects in the *A* area. This constraint is also soft and can be relaxed by associating the value with the variable $L_p^{(t)}$.

$Quota^{(t)}$ is a continuous variable that represents the minimum quota allocated to the area $a \in A$. The value of the quota for an area depends on two factors: (i) the total resources used in the stage t - $\sum tn_e^{(t)}$; and (ii) the minimum value needed to execute all the projects in the area considering the cheapest execution mode $cmin_a^{(t)}$ (Equation 19). Considering $\beta \in [0, 1]$ a constant that determines the percentage of the total resources used reserved for the area, Equation 20 defines the value of the quota of an area and the constraints 16 and 17 linearize this value to define the feasibility region $U^{(t)}$ with the help of the binary variables $mn_a^{(t)}$.

$$cmin_a^{(t)} = \sum_{p \in P_e^{(t)}} min_{m \in M_p^{(t)}} \{c_{m,p}^{(t)}\}, \qquad \forall a \in A \ (19)$$

$$Quota_a^{(t)} = \min\{\sum_{e \in E} \beta * tn_e^{(t)};\ cmin_a^{(t)}\}, \qquad \forall a \in A \ (20)$$

Lastly, the maximum amount of budget available should be used. Thus, the constraint 18 imposes that the sum of the amount of resources allocated along the funnel must be less than or equal to the total budget.

2.4 Transition

The $f_T(s, u, \omega)$ transition function of the problem is multidimensional and determines how the system evolves from one decision stage to another. It determines the dynamics of the process as a whole. In addition to the current stage s, transition depends on the decision u and the realization of the uncertainty ω for the next stage, as shown in Equation 21.

$$S^{(t+1)} = f_T\left(S^{(t)}, u^{(t)}, \omega^{(t+1)}\right) \qquad (21)$$

For the presented problem, the decision defines changes in the set of projects $P^{(t)}$ when defining who will be executed, frozen or canceled. This set is also altered by the realization of uncertainty due to the arrival of new projects and the possibility of stage change of the projects, in case of development success.

Figure 2 details the transition between the sets $P_e^{(t)}$. There are five transition situations for an element between sets $Pe^{(t)}$. Firstly, new projects arrive (*arrival*) in the first step of the funnel, and only when they are in the last stage of funnel, can be released in the market (*launch*). At any stage, there are 3 possibilities: (i) case 1 occurs when the project is executed but does not end the development time in the current step, or when it is frozen; (ii) case 2 occurs when the project is executed and finalizes the time required for development in the step; and (iii) finally, the project leaves the development funnel if it is canceled.

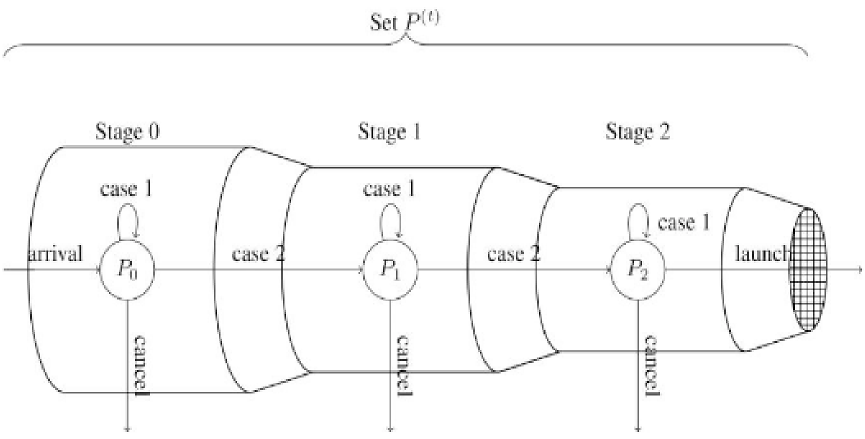


Figure 2: Transitions on development funnel

Source: Authors.

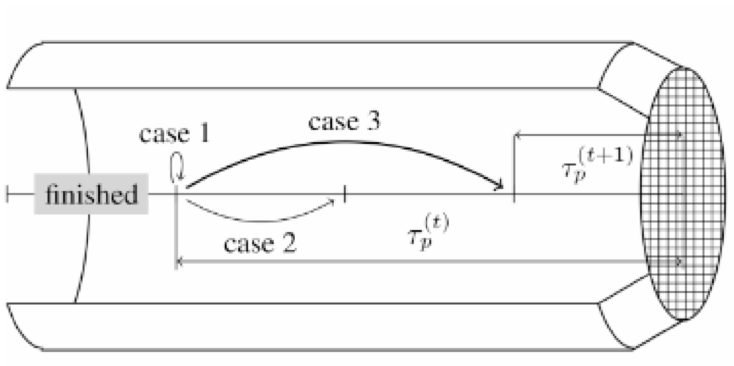


Figure 3: Transitions inside a stage on the development funnel

Source: Authors.

Each existing project undergoes individual changes with both the decision and the un- certainty. Firstly, if the project has been executed, the residual time required for the step change represented by $\tau_p^{(t+1)}$ is changed according to the execution mode and over current residual time (22). Figure 3 details the possibilities of transition for the residual time of a project in a given fase. Case 1 occurs when the project is frozen or when its execution delays in the period. The most common case, case 2, occurs when one chooses an execution mode that will reduce τ_p as expected, that is, the same magnitude of the interval between decision stages. Finally, when the project is executed without delay, with a mode in which it is possible to accelerate development, the magnitude of the reduction of residual time may be greater than the time between the decision stages. For the example of the figure, $\tau_p^{(t+1)}$ was obtained after case 3.

$$\tau_p^{(t+1)} = f_T^1\left(m_p^{(t)}, \tau_p^{(t)}, \omega^{(t+1)}\right) \qquad (22)$$

Another dimension of the project that is affected by the decision and the uncertainty during the transition is the expected performance that the project will achieve at the end of its development.

This parameter models the expectation assessed by the development team regarding performance. When executing the project, the execution mode guides this parameter because it is associated with an action plan, and the higher the resource contribution, the greater the probability that the performance will be better. In the model of this study, for each mode, a probability of success $Psucesso_m^{(t)}$ was associated for the execution of a phase of the project and a magnitude of variation $\delta_m^{(t)}$ for gain (loss) of performance in case of success (failure).

The other parameters depend only on uncertainty. The return parameter of a project at the time of launch $R_p^{(t)}$ is reparameterized after uncertainty is realized with new exogenous market information. It is possible to model the dependency between the return of projects through this parameter. The definitions of the execution modes for each project can be updated but also depend only on the uncertainty as well as the budget available for the next decision stage.

3 I HEURISTIC POLICIES

In this section we present two heuristic policies that will be tested through simulation within the framework of the stochastic dynamic programming model described in Section 2. The developed model will be used to find the value of being in a state given a fixed π policy (see Equation 2).

The heuristics were developed for illustrative proposes so, outstanding results are not expected. The heuristics are not totally myopic policies as they try to look ahead in some sense. In other words, they try to estimate future information in order to help the decision process. A difference between the policies is the procedure used to decide. The first one defines the decision variables through an adapted MIP problem. Accordingly, the second one uses a greedy procedure to solve the problem.

3.1 Heuristic Policy I – *mip* (HPI-mip)

The first policy is to solve the problem by executing at each stage the decision model defined in the equations 11 to 18, but with the objective function defined by the expression 23. Relative to Bellman's Optimality Equation (expression 10), the HPI-mip policy differs by the format of its objective function. In order to anticipate the future (look ahead), we account for every project under development the estimate of its NPV based on current information and considering only the return ($r_{m,p}^{(t)}$) and the minimum residual cost required for its development ($cr_{min,p}^{(t)}$).

$$\max \sum_{p \in P^{(t)}} \sum_{m \in M_p^{(t)}} \left(r_{m,p}^{(t)} - cr_{min,p}^{(t)} \right) * w_{m,p}^{(t)} - \sum_{a \in A} \rho_1 * L_a^{(t)} - \sum_{e \in E} \sum_{p \in P_e^{(t)}} \rho_2 * J_{e,p}^{(t)} \quad (23)$$

3.2 Heuristic Policy Ii – greedy (HPII-g)

A second policy (HPII-g) has been developed, which consists of choosing, in a greedy manner, which projects will be executed at each stage. The Algorithm 1 summarizes the operation of the cited policy.

PHII-g ():

1 **for** $p \in P$ **do**
2     $m_p^* = \arg\max_m Npv_p(m,p)$
3   **if** $Npv_p(m_p^*) > 0$ **then** Insert p in $ExecList$ by decreasing the Npv_p
4   **else** Cancel the project p
  end
5 **for** $p \in ExecList$ **do**
6   **if** $c_{m_p^*,p} \leq budget$ **then**
7         $budget = budget - c_{m_p^*,p}$
8   Execute p with mode m_p^*
9   **else if** $(p \in P_c) \& (Cong_p > 0)$ **then** Freeze the project p
10   **else** Cancel the project p
  end
end

Algorithm 1: Heuristic Policy II - greedy

Source: Authors.

In an initial moment, for each project *p*, the mode of highest NPV (line 2) is computed, and thus the projects are inserted in an ordered (descending) form in a list (ExecList) if the NPV is positive (Line 3). Subsequently, a procedure runs through the list, testing the feasibility of executing projects by looking only at the budget available at the stage (line 6) and, if the project can be executed in the previously chosen mode, the budget is deducted (line 7) and execute the project (line 8). Otherwise, if *p* is preemptive, the project is frozen (line 9). Finally, non-executed and non-frozen projects are canceled (lines 4 and 10). It is important to note that the PHII-g does not consider the *soft* constraints of the portfolio.

4 I COMPUTACIONAL TESTS

There were randomly generated, 8 instances divided in two scenario groups of parameters and 4 groups of dimension of the problems. The tests were conducted utilizing a Acer Aspire *E*5 – 471 computer with Intel(R) Core(TM) *i*3 – 5005*U*, 2.00 GHz processor, 4 Gb of RAM and Windows 10 operating system.

For use of the model, it was implemented in Python 2.7 a simulator that generates, at each stage, all the information referring to the uncertain parameters, including the data reffering to new projects that arrive in the system. After the decision taken based on a specific policy, the simulator realizes the transition from one state to another. For a better utilization of the space destined for the essay, the description of the generation of uncertainties will be omitted.

However, all the utilized instances, as well the implemented codes, can be solicited to the authors for replication and, beyond that, after publication of the final results of the research, the same will be available.

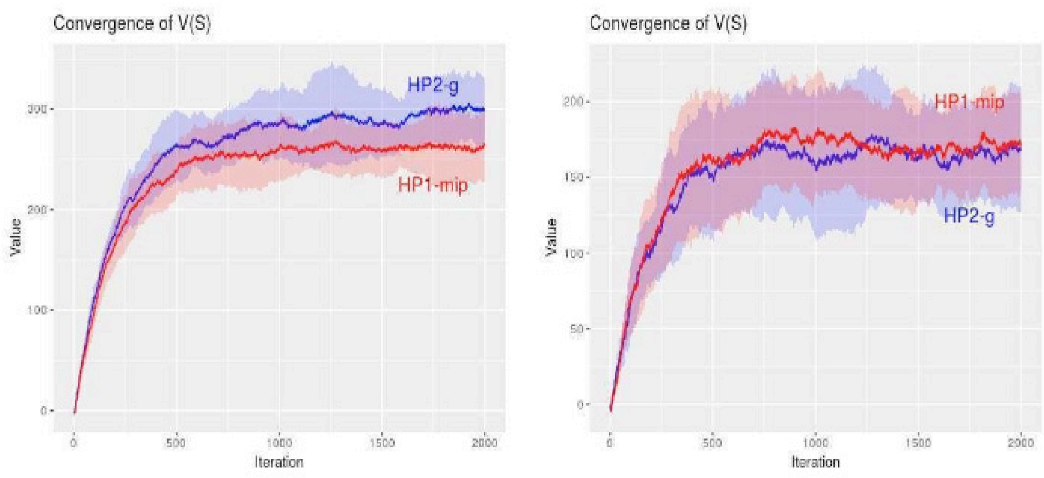
It is important to highlight that the proposed function Silva e Santiago (2009) was used for the modeling of the return obtained after the launch of the project, once that it has the capacity to englobe all the uncertainties referred to developing projects defined by Huchzermeier e Loch (2001).

Scenarios 1 and 2 differentiate themselves in two ways: (i) in terms of cust - by the penalty parameters of the soft constraints of a minimum quota per area (ρ_1) and the concentration of resources in a single project per stage of development (ρ_2); and (ii) by alteration of the amplitude of return variation of each project.

- Scenario 1: is represented by low penalty costs, being the attributed values for ρ_1 and ρ_2, respectively, 2 and 4. The configuration of the parameters for the generation of income of a project determines, in this scenario, a maximum return of 3.5 times the total cost of the project, being able to vary from zero to a maximum of 7 times the total cost of each project;
- Scenario 2: Possess significantly elevated penalty costs, having values for ρ_1 and ρ_2 of, respectively, 100 and 120. For each project it is generated a maximum return of, on average, 4 times the total cost, being able to vary from zero to a maximum of 8 times the total cost of each project.

The rate of arrival of new projects inserted in each stage was also varied. The arrival rates were separated into four groups: (i) 3 projects, (ii) 6 projects, (iii) 9 projects and (iv) 12 projects. Five replications were assigned for each scenario. The random number generator seed of the simulator was alternated with each run.

The Graphs 4(a) and 4(b) show the convergence of the exponential smoothing for the value $V(S)$ for each of the policies in the instances of size 3, on the scenarios 1 and 2, respectively. There are no visual evidences that show a difference in convergence rates for each of these methods.



(a) i3cen1 instance (b) i3cen2 instance

Figure 4: Convergence of the exponential smoothing for the value $V(S)$

Source: Authors.

The results of the tests with the instances can be found on the Table 1. The first column refers to the name of the instance, the next three column present the average of the estimated value for the policy HPI-mip, its confidence interval and the average time of execution, and finally, the same information for the HPII-g policy. It should be noticed that the policy PHII-g has excelled on 5 of 8 instances tested. In three cases, i3cen2, i6cen2 and i9cen2, the expected values for two policies were within the confidence interval of each other, not being possible to concluded about the difference of performance without the realization of a bigger number of replications.

We believe the main reason for HPII-g outperforming HPI-m is related to the quality of return estimation of each project, once HIP-m uses a naive approximation of the real value and HPII-g works with a more accurate approximation. This fact demonstrates the value of information in stochastic dynamic environments.

Alternatively, in terms of computational time, the policy HPII-g has shown to be more costly. However, this comparison is not adequate due to the fact that the policy HPI-mip uses the Gurobipy API to resolve the optimization subproblem, which is programmed in parallel.

	PHI-L			PHII-g		
Instance	Mean	95% CI	t(s)	Mean	95% CI	t(s)
i3cen1	265.35	(229.19 ; 301.51)	59.3	299.75	(268.52 ; 330.98)	15.3
i3cen2	172.21	(141.44 ; 202.99)	66.8	168.4	(126.08 ; 210.72)	16.4
i6cen1	294.5	(261.06 ; 327.94)	102	351.31	(309.54 ; 393.09)	171
i6cen2	224.85	(184.11 ; 265.6)	98.7	237.2	(190.75 ; 283.65)	193.2
i9cen1	284.79	(254.68 ; 314.9)	136.9	376.84	(329.38 ; 424.31)	500.2
i9cen2	211.16	(172.62 ; 249.7)	118.3	252.18	(198.54 ; 305.82)	449.4
i12cen1	252.79	(206.26 ; 299.31)	172.0	398.05	(346.02 ; 450.07)	909.2
i12cen2	175.91	(145.36 ; 206.46)	182.6	279.55	(212.96 ; 346.15)	902.3

Table 1: Instances Results

Source: Authors.

5 I RESULTS AND DISCUSSIONS

The present study has addressed the project resource selection and allocation problem in an innovation funnel and provides, as it's principal contribution, the development of a stochastic dynamic programming problem to represent this situation. In this vein, the value of this contribution is given as the model has important characteristics that are taken into account in the context of in- novation companies, such as dynamicity, uncertainty in returns and, in the process of development, the multiple modes of execution and possibility of preemption.

Moreover, the implementation of a simulator based on the proposed model generates a framework for comparison of policies, as realized by the policies named HPI-mip and HPII-g. The presentation of such policies, given that they are able to solve the problem, is also a minor contribution. Note that for the instances tested with the HPII-g heuristic excels over HPI-mip, which suggests that the quality of the estimation of future information may be more impactful on performance then the subproblem solving approach.

Finally, for future studies, importance is given to the development of policies that are capable of better exploring the information of the current state. A possible way would be through the solution of the problem using approximate stochastic dynamic programming techniques (see Powell (2007)).

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Agência Brasileira do ISBN
ISBN 978-85-7247-478-8
9 788572 474788