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Project Portfolio Optimization under Temporal Constraints with uncertainty

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Abstract

The definition of more realistic scenarios of instances for the Project Portfolio Optimization (PPO) of new product developments usually should involve precedence relations that generate effects related to time-interdependence among different projects. The study of time -interdependences, or time effects, on the selection of projects captures our attention because they affect the problem objective functions. Three different moments have been identified as usually present in any project: 1) the estimated completion time; 2) the moment in which the competence become significant; and, 3) the moment in which the developed product becomes old. A PPO under such temporal constraints (denoted PPOTC) could face risk because the lack of reliable data derived from long lead times of projects, or by a complex market and technology dynamics; such imperfect knowledge could cause variability in the benefits and requirements of a PPOTC. In this sense, this research proposes the design of a methodology based on intervals for PPOTC under uncertainty, and the study of their influence in choosing optimal project portfolios of new product developments. The advantage of this approach is a unified and simple way to model the different sources of imprecision, uncertainty and arbitrariness. Also, the model is parametrized such that the attitude of the DM facing the imperfect knowledge can be adjusted by using two meaningful parameters.

Keywords: Decision Aid; Time-Interdependence; Imperfect Knowledge.

Introduction

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The development of competitive new product is likely the most important factor that allows manufacturing enterprise surveillance within a competition environment (Wei and Chang, 2011). To a great extent, a successful new product development (NPD) can produce large benefit (profit, prestigious, market occupation, etc.), but needs complex management and involves high risk, mainly due to the fast changing and conflicting environment, as well as technological innovations. Since there are more good projects than resources for them, the decision makers should select appropriate NPD project portfolios, expecting that these portfolios allow to develop several, even many, attractive and successful products that generate growing benefits (Salo et al., 2011). To balance risk and potential benefits is a crucial aspect in selecting appropriate new product development portfolios (e.g. Loch and Kavadias, 2002). we can distinguish two main sources of imperfect knowledge that produces risk:

(i) Uncertainty due to the risk inherent in the future (e.g. uncertain market payoffs, irruption of product competitors, increment of costs) which causes variability in the benefits and requirements of the NPD projects.

(ii) Non-stochastic imperfect knowledge related to the imprecision and arbitrariness of project data, portfolio measures, and available resources.

Different approaches have been proposed to handle uncertainty in the general context, the type of them ranges from the use probabilistic models and/or fuzzy sets, cf. (e.g. Hasuike et al., 2009; Damghani et al, 2011), to the interval analysis (cf. Fliedner & Liesio, 2016; Liesio et al., 2007). Particularly, on Project Portfolio Optimization under Temporal Constraints (or PPOTC), some of the most recent advances tackle the problem of uncertainty using fuzzy logic (Relich and Pawlewski, 2017; Wei et al., 2016), constraint satisfaction models (Relich, 2016), probabilistic models (Badizadeh and Khanmohammadi, 2011), or interval mathematics (Liesio et al., 2008; Balderas et al., 2016; Toppila & Salo, 2017).

Based on the revised scientific literature, so far, the PPOTC in NPD has not considered the time effects over the criteria values of the projects. Even though time effect uncertainty has been managed (through intervals for example), the strategies defined to handle the impact in objectives of individual projects that forms a portfolio remains as an area of research. The relevance of such study is due to time effects always appears during the lifespan of a project, affecting its conditions and impact in the end in the retribution it provides. Some of the causes of benefits reduction for a project are the presence of competing projects or because the project has completely lost its relevance. The consideration of such situations can alter the formation of portfolio, and hence, it becomes an important area of interest to solve the PPOTC in NPD.

This research is primarily oriented to the modelling of three specific time-related effects, under imperfect knowledge, and their influence in choosing optimal NPD-oriented project portfolios. The time effects are related to three different moments that are usually present in any project j: 1) the estimated completion time, denoted $\boldsymbol{end_j}$; 2) the moment in which the competence become significant, denoted $\boldsymbol{competence_j}$; and, 3) the moment in which the developed product becomes old, denoted $\boldsymbol{old_j}$. The proposed strategy is an interval-based method for the PPOTC related to the NPD portfolio optimization problem under the above forms of imperfect knowledge. This approach has the advantage of a unified and simple way to model the different sources of imprecision, vagueness, uncertainty and arbitrariness. The attitude of the DM facing the imperfect knowledge is adjusted by using some meaningful parameters.

Materials and Methods

Figure 1 presents a general scheme that describes the common situation present in PPOTC on NPD Projects, and a guide to its solution. First, it considers the four factors that are usually involved, which are the value of the products, the information of the customers and market, and the time effects. All these factors are integrated into an optimization model, which in turn can be solved by evolutionary approaches, i.e. approximated strategies that achieve good solutions spending a reasonable amount of time. The solution by evolutionary approaches should also involve a selection process to choose one of the distinct portfolios that can be constructed by them, such portfolio is the Best NPD portfolio that can be reported as the solution for the problem.

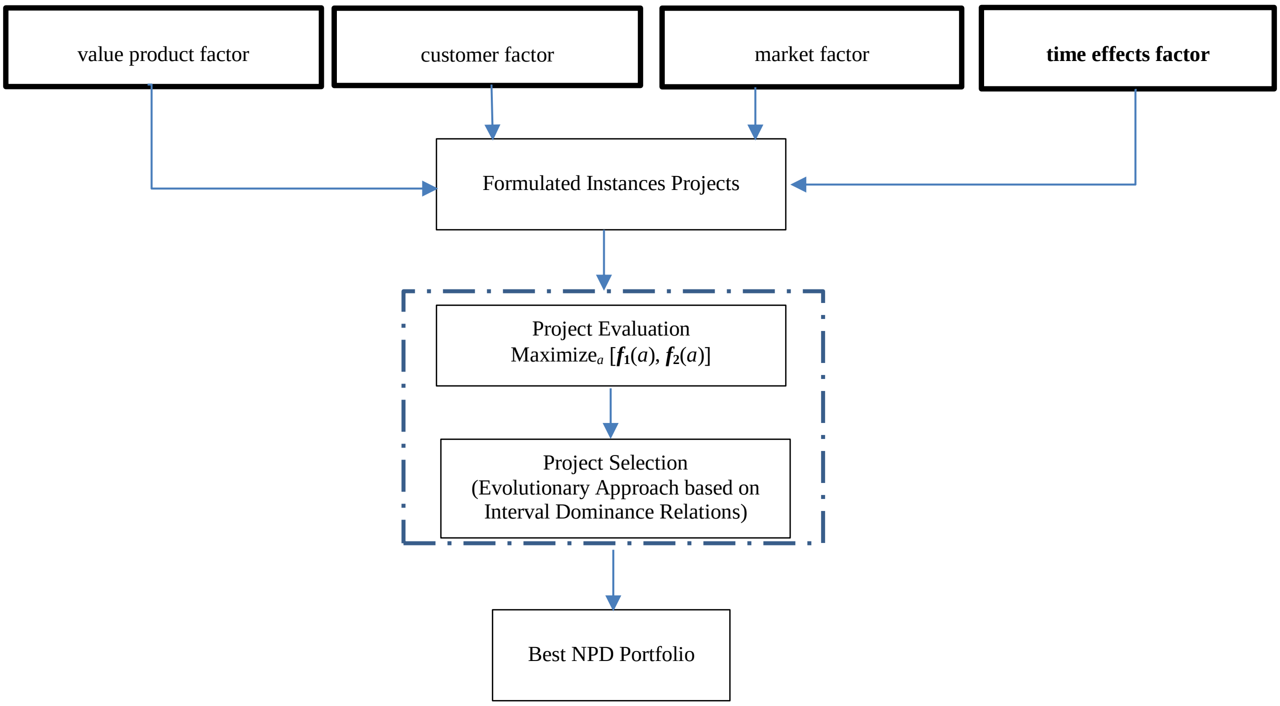

Figure 1. General scheme of solution of PPOTC on NPD.

The R&D project portfolios generic optimization model might be represented as an interval multi-objective optimization. One possible approach is the model presented in Equation 1, a model based on well-known formulations of project selection that has been broadly studied in the literature (e.g. Stummer and Heidemberger, 2003; Fernandez & Navarro, 2005; Kremmel et al., 2011; Amiri, 2012; Klapka et al., 2013; Cruz et al., 2014).

$$\text{Maximize}_a\ [\boldsymbol{f}_1(a), \ldots \boldsymbol{f}_N(a)] \tag{1}$$

s.t.

$$\begin{array}{ll}
\boldsymbol{R}_k(a) <\approx \boldsymbol{P}_k & \forall\ 1 \le k \le n_r \\
\boldsymbol{start}_j = 0, & \text{for all } j \text{ such that } a_j = 1, \text{ and } P_{a,j} = \varnothing \\
\boldsymbol{start}_j >\approx \text{Max}\ \{\boldsymbol{start}_i + \boldsymbol{end}_i \mid i \in P_{a,j}\}, & \text{for all } j \text{ such that } a_j = 1 \\
\boldsymbol{start}_j + \boldsymbol{end}_j <\approx \boldsymbol{old}_j & \text{for all } j \text{ such that } a_j = 1
\end{array}$$

where $a = < a_1, a_2, a_3, \ldots, a_M >$ is a binary vector that represents a portfolio, i.e. is a subset of projects where a_i=0 means that project i will not be financed, and a_i=1 means that the project receives support; the vector of the impacts $\vec{f}(a)$ of portfolio a is associated with N objectives $\vec{f}(a) = < f_1(a), f_2(a), \ldots, f_N(a) >$. The functions $\boldsymbol{f}_i(a)$ are the accumulated impacts of the portfolio a. The constraint $\boldsymbol{R}_k(a) <\approx \boldsymbol{P}_k$ limits the consumption of resource $\boldsymbol{R}_k(a)$ by the portfolio a to the total available resource $\boldsymbol{P}_k$. The times $\boldsymbol{start}_j$ and $\boldsymbol{end}_j$ are the start and end of a project, while $\boldsymbol{old}_j$ is the time that if extended the project j will no longer have any impact in at least one of its objectives. Finally, the symbol "≈" means "with sufficient likelihood". Note that the model presented in Equation (1) is based on intervals, denoted by variables in bold, and the interval definition and its operations were taken from (Balderas et al., 2016).

The model in Equation (1) should also consider the effect of competence. To do so, it is proposed to change the values of the objectives $\boldsymbol{f}_i(a)$ of a project j in the presence of competence before solving the optimization problem in Equation (1). In other words, whenever $\boldsymbol{competence_j}$ be smaller than $\boldsymbol{end_j}$ the value of $\boldsymbol{f_i}(a)$ should be reduced by a fraction that represents the impact of the presence of competence during the lifespan of a project.

The previous model represents a way to evaluate projects and considering the time effects. The selection process can be performed through evolutionary approaches that could handle intervals in its construction process (cf. Balderas et al., 2016). The evolutionary approaches deliver a set of solution that approximates the Pareto frontier; while it is common that more than one solution in such set has similar dominance condition, it is uncommon that a Decision Maker could work with multiple portfolio. For such a case, a final performance metric should be designed that allows the ranking of the set provided by the algorithm and allows to choose one as the best NPD portfolio.

Results and Discussion

In order to test the previous approach, instances of PPOTC on NPD should be constructed. This section presents an algorithm to build them and analyze the possible outcomes of its solution.

A single instance of PPOTC on NPD can be characterized by: 1) the available budget $\boldsymbol{P}$ with imperfect knowledge involved; 2) the number N of involved objectives; 3) the number of involved projects M; 4) the cost $\boldsymbol{cost_j}$ and the objective value $\boldsymbol{f_{i,j}}$ for each project j and objective i; 5) the time effects $\boldsymbol{end_j}$, $\boldsymbol{competence_j}$, $\boldsymbol{old_j}$ defined for each project j; and 6) the degradation ω_i for each objective $\boldsymbol{f_i}$ that should be applied in case that the competence of a project appears before it ends. Let us recall that all the bold variables involve information with uncertainty expressed by intervals. Table 1 presents a brief example of such an instance, note that this instance only will apply degradation to the first objective of a project j if $\mathbf{competence_j}$ is smaller than $\boldsymbol{old_j}$; also note, that as commented before, it is required the use of interval operations to add intervals and compare them.

Table 1. PPOTC on NPD instance with M=4 projects, N=2 objectives, and available budget $\boldsymbol{P}$=[100, 120].

Project j	$\boldsymbol{cost_j}$	$\boldsymbol{f_{1,j}}$*	$\boldsymbol{f_{2,j}}$	$\boldsymbol{end_j}$	$\boldsymbol{competence_j}$	$\boldsymbol{old_j}$
1	[60,62]	[12,17]	[90,95]	[5,8]	[7,8]	[7,9]
2	[40,45]	[10,19]	[108,115]	[1,5]	[2,3]	[3,5]
3	[50,57]	[12,15]	[50, 120]	[7,10]	[7,8]	[8,9]
4	[48,60]	[14,20]	[80, 100]	[3,4]	[3,4]	[3,5]

* The fixed degradation percentage ω_1 for objective 1 is 25%

Algorithm 1 shows the pseudocode used to generate one random instance for PPOTC on NPD similar to that in Table 1. This strategy extends an existing instance of PPOTC on NPD with intervals to include the uncertain time effects associated with the events of project completion $\boldsymbol{end_j}$, project obsolescence $\boldsymbol{old_{,j}}$, and the apparition of competence $\boldsymbol{competence_{,j}}$. This algorithm uses the possibility measure $Poss(\mathbf{A} \geq \mathbf{B})$ that and interval be greater than or equal than another; this measure, as defined in other approaches based on intervals, uses a threshold δ in order to satisfy the condition *greater than or equal*. The variants in the use of such threshold arises in two configurable parameters of the proposed model, one of them to adjust the level of conservatism of a decision maker with regard to the use of resources, the other with respect to quality of the objectives desire, both features expressed as intervals.

Algorithm 4.1. PPOTCNPDInstanceGenerator

Input: ***P***, *N*,*M*– The available budget and the numbers of objectives and projects, respectively.

Input: *I* – An array of *M* projects, where each project *j* contains = {$\boldsymbol{cost_j}$, $\boldsymbol{f_{1,j}}$, $\boldsymbol{f_{2,j}}$}.

Input: ε_1, ε_2, ε_3 – The amoung of projects that are feasible, degraded or obsolete, where $\varepsilon_1+\varepsilon_2+\varepsilon_3=M$.

Input: δ – Threshold of conservatism

Output: (I_{ext}, ω_1) – A tuple containing the array I_{ext} with the *M* projects having each project *j* the values of {$\boldsymbol{cost_j}$, $\boldsymbol{f_{1,j}}$, $\boldsymbol{f_{2,j}}$, $\boldsymbol{end_j}$, $\boldsymbol{old_j}$, $\boldsymbol{competence_j}$}, and ω_1.

```
C_ε1, C_ε2, C_ε3 ← 0
for j=1 to M do
    V_c ← Random(1,10)
    end_j ← [V_c, min{10, V_c + Random(1,4)}]
    V_comp ← max{0, min{10,V_c+Random(-3,3)}}
    competence_j ← [V_comp, min{10, V_comp + Random(1,4)}]
    V_old ← V_comp+Random(0,2)
    old_j ← [V_old, min{10, V_old + Random(1,4)}]
    if Poss(old_j > competence_j) > 0.5 then
        if Poss(competence_j ⩾ end_j) ⩾ δ then
            if C_ε1 + 1 <= ε1 then
                I_ext[j].end_j ← t_c,j
                I_ext[j].competence_j ← competence_j
                I_ext[j].old_j ← old_j
                C_ε1 ← C_ε1 + 1
            else
                j ← j – 1
            end if
        else if Poss(end_j ⩾ t_endj) ⩾ 1 – δ then
            if C_ε2 + 1 <= ε2 then
                I_ext[j].end_j ← end_j
                I_ext[j].competence_j ← competence_j
                I_ext[j].old_j ← old_j
                C_ε2 ← C_ε2 + 1
            else
                j ← j – 1
            end if
        else
            if C_ε3 + 1 <= ε3 then
                I_ext[j].end_j ← end_j
                I_ext[j].competence_j ← competence_j
                I_ext[j].old_j ← old_j
                C_ε3 ← C_ε3 + 1
            else
                j ← j – 1
            end if
        end if
    end if
end for
ω1 ← Random(0.1, 0.4);
return (I_ext, ω1)
```

Finally, one way to compare solutions is by means of an indicator that measure the number of feasible projects that remains in the portfolio after considering the time effects. For example, Table 2 shows what would be a comparison among two solutions, row *A* contain a possible solution obtained from solving Equation 1 using algorithms such as Grey-NSGAII (Balderas et al., 2016), and row *B* contain a solution obtaine by sampling the time effects over solutions without considering them a priori in the solution strategy. It is expected that a solution to Equation 1 with a high level of conservatism will yield portfolios with lesser values in the objectives, however, given that this approach consider apriori the time effects, the portfolio are more robust, and hence, it is more probable that more feasible project remains even after time effects occur. The last two columns of Table 2 present the indicator of the latter comment, **Card* is the number of projects in the portfolio built, and *C1* are the projects that remain feasible (or actives, with impact) after time effects have been considered.

Table 2. Portfolios of NPD with a high level of conservatism.

Id	Costo		Obj 1		Obj 2		*Card	C1
A	239880	249680	988032	995627	256481	263721	33	18
B	239800	249900	1353225	1362125	309055	319155	38	14

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Conclusions

The present research presents a methodology of solution for the problem or Project Portfolio Optimization with Temporal Constraints on New Product Developments (PPOTC on NDP). The methodology manages risk and uncertainty through intervals, and incorporates the uncertainty derived from time effects. Also, it allows to adjust the level of conservatism of a decision maker in the budget spent and in the profits gain through the comparison of intervals using different thresholds. Finally, it analyze a way to compare solutions derived from the present approach that involves a priori and during the search process the time effects, against does that does not consider them in the same way.

The area of research continues with a further development of the strategies, indicator, and experiments, in order to show stronger evidence of their performance.

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