This paper was presented at The XXIII ISPIM Conference – Action for Innovation: Innovating from Experience – in Barcelona, Spain on 17-20 June 2012. The publication is available to ISPIM members at www.ispim.org.

A real options based support system to open innovation

Giovanna Lo Nigro*

University of Palermo, Viale delle Scienze, 90128 Palermo, Italy.
E-mail: giovanna.lonigro@unipa.it

Azzurra Morreale

University of Palermo, Viale delle Scienze, 90128 Palermo, Italy.
E-mail: azzurra.morreale@unipa.it

* Corresponding author

Abstract: Pharmaceutical R&D process (PR&DP) has been deeply investigated by different streams of literature; the interest is due to the strategic implication of the related decisions undertaken. The PR&DP has been revolutionised by the biotech advent and as a consequence R&D managers cannot avoid to consider Open Innovation paradigm during this decision process. Starting from a Real Option optimization model available in literature, the paper aims at proposing a decision support system (DSS) able to suggest the candidate products to be included in the best R&D portfolio varying input parameters (resilient products), to provide a products Pareto analysis that aims at individuating the products for which it is worthwhile to acquire a deeper input parameters knowledge and to draw *what if* rules. The proposed DSS has been applied to a numerical example available in literature and research findings show interesting managerial and academic implications.

Keywords: Open Innovation, Biopharmaceutical industry; R&D portfolio; DSS; Real Options

1 Introduction and problem statement

Pharmaceutical firms struggle to discover and develop promising compounds before competitors do: this will guarantee them to beat competitors in the winner-takes-all patent race and, once the drug is introduced in the market, to gain great revenues useful also to fund other R&D projects. Thus, due to its focus on innovation, R&D process is extremely important in pharmaceutical industry, as it allows a company to achieve high profits and growth rates. This importance is witnessed by the financial effort that pharmaceutical firms carried out during the last decades to fund R&D activities. In 2009, pharmaceutical companies invested US$ 65,3 billion in R&D, 37% more than 5 years before (Phrma 2011).
Pharmaceutical industry has experienced the biotech newcomers advent that foster the Open Innovation (OI) solutions because of the increasing need of collaboration in order to exploit the complementary resources of incumbents and newcomers.

The PR&DP is time and money consuming, it is uncertain and it can be accomplished following different alternatives in the continuum between hierarchy (in house development) and market (outsourcing R&D), passing through different kinds of alliances. As a result, the pharmaceutical R&D decision making process is very challenging because it involves different literature topics: R&D evaluation, portfolio selection and Open Innovation.

Moreover, PR&DP has a long and dynamic life and further investments depend on the success/failure of the previous ones then it is an ideal field of application for Real Options Analysis (ROA). ROA is acknowledged as a powerful tool to evaluate uncertain projects that have an intrinsic flexibility; so, as Vanhavarbeke *et al*. (2008) state, it is surprising that scholars do not pay attention to the existing synergy between ROA and OI. On the other hand ROA implementation, as widely demonstrated in literature, is narrowed to very limited cases because of its perceived complexity (Hartmann and Hassan, 2006). Debate about Real Otpions definition is still open among scholars: we refer to the study of McGrath *et al*. (2004) that gives a very comprehensive definition, and starting from their conclusions we can affirm that R&D pharmaceutical process is a suitable field of application for ROA as it consists of "specific investments with option-like properties". Literature overview offers an interesting example of mathematical models, based on ROA, able to support managers in the selection of the best R&D portfolio (Rogers *et al*., 2002; Rogers *et al*., 2005; Lo Nigro *et al*., 2012); however, these methods do not support managers in a *what if* analysis able to understand what happens to the best solution if some parameters should change, and this is not an unlikely possibility due to the uncertainty that characterises the R&D process. The paper's purpose is to assess a heuristic DSS based on a Real Options optimisation model (Lo Nigro *et al*., 2012) that allows to select the candidate products which should be developed in order to maximize the economic value of the portfolio estimated through its Real Options Value. The proposed DSS provides some insights about the change in the optimal solution due to the change of some input parameters. The paper is organised as follows: the following section, starting from the literature analysis of portfolio selection and real option models based on portfolio selection, sets the paper's contribution; section 3 introduces the research methodology and the numerical example we will refer to; section 4 illustrates the obtained results and shows how the DSS is structured; at the end, section 5 focuses on paper findings and further developments.

2 Portfolio selection literature overview and research contribution

Portfolio selection is the problem of allocating capital over a number of available assets in order to maximize the return on the investment while minimizing the risk. (Goldfarb and Iyengar, 2003). The portfolio selection problem has been one of the most important issues in modern finance since the 1950s. The first model for portfolio optimization was developed by Markowitz in 1952; in this model, the return on a portfolio is measured by the expected value of the random portfolio return, while associated risk is quantified by the variance of returns' distribution. In his study, Markowitz, in order to obtain an efficient portfolio, shows how to calculate portfolio which has the highest expected return for a given level of risk, or the lowest risk for a given level of expected return.

Dickinson *et al*. (2001) and Chien (2002) provide an overview of this literature topic: the concept of building business portfolios emerged in the late 1950s and evolved through the 1970s (Souder and Mandakovic, 1986) to become an established planning tool. In the 1980s and 1990s, companies extended the use of portfolio management into new

products selection and R&D resource allocation. Many theoretical and practical attempts have been made to develop models that would support the process of R&D portfolio selection. Early attempts focused on theoretical operations research and management science models, usually in the form of a constrained optimization problem (Eilat *et al*. 2006).

Many papers have surveyed the existing literature on R&D portfolio selection models: in particular Chien (2002) includes a survey of selection procedures and shows that several originated from Markowitz's work.

According to many scholars, R&D portfolio selection consists in selecting, from a given set of candidate projects, a subset of projects, to maximize an objective function without violating the constraints (Baker, 1974; Liberatore and Titus, 1983; Liberatore, 1988; Danila, 1989). However, the suggested models to deal with this problem have not found widespread use in practice. This phenomenon was observed by Hall and Nauda (1990) who noticed that these models require accurate data that are unavailable in most cases. The same phenomenon was also observed by Schmidt and Freeland (1992) and later confirmed by Cooper (2001). Farrukh *et al*. (2000) offer possible explanations for the limited implementation of such models in practice and Loch *et al*. (2001) describe a similar experience in a real-world setting.

Moreover Baker and Freeland (1975) emphasized a drawback of many selection models. In their review of existing methods at that time, they concluded that ''one of the most important limitations of present R&D project selection models is the inadequate treatment of project interrelationships with respect to both value and resource utilization.'' Not much has changed since then.

The problem of interactions among projects received relatively little attention in literature. Most of the existing studies select R&D projects by evaluating individual projects. However, according to Keeney 1987, the combination of individually good projects unnecessarily constitutes the optimal portfolio.

Several authors remark, in fact, that it is better to evaluate the entire R&D project portfolio of a company instead of its single projects, in order to consider the relations and the interdependences between them. These interdependences, ignored if projects are evaluated one by one, usually deal with limited resources consumption, risk balancing and company strategies.

In his study, Chien (2002) shows a summary of existing studies on the interrelation between projects. The author identified several types of interrelation: outcome/context/budget interrelation, (Weingarten, 1966); overlap in resource utilization, technical or effect interdependence (Aaker and Tyiebyee, 1978); internal and external relationships (Gear and Cowie, 1980); cost/outcome /benefit interrelation (Fox *et al*., 1984)

Moreover, according to Dickinson *et al*.'s study (2001), the R&D project selection model can be divided into three categories :

1. *Mathematical programming*;
2. *Classical tools* that include scoring and sorting models and checklists. These methods maximize the value of the portfolio through either financial or non-financial measures.
3. *Mapping tools*. Mapping portfolio tools use graphical and charting techniques to visualize a balanced portfolio. Two-axis diagrams are typically used to display the trade-off between two criteria: e.g., risk versus reward, probability of success versus value, or ease of implementation versus attractiveness.

In recent years, complex and ad hoc models were developed to capture the actual situation of R&D project selection. Beaujon *et al*. (2001) developed a mixed integer programming model, in the form of a multi-dimensional problem, to find an optimal

project portfolio and studied the concept of partial funding project and the sensitivity of an estimated project value to the selected portfolio. Dickinson *et al*. (2001) demonstrated the use of a dependency matrix representing complex interactions between projects and developed an optimal portfolio model, over multiple time periods, that was developed for the Boeing Company. Moreover Eilat *et al*. (2006) developed a methodology for the construction and analysis of efficient, effective and balanced portfolios of R&D projects with interactions; the methodology is based on an extended data envelopment analysis (DEA) model that quantifies some the qualitative concepts embedded in the balanced scorecard (BSC) approach.

Computer-based DSS combines the different approaches into an integrated, interactive, manager-friendly tool: computer-based DSS can then be used directly by decision makers to analyze *what if* scenarios for a different parameters set and portfolio compositions (Henriksen and Traynor, 1999). Chu *et al*. (1996) developed a DSS to help managers to select the most appropriate sequences of plans for product research and development (R&D) projects that have strict constraints on budget, time, and resources. Moreover Ghasemzadeh and Archer (2000) discussed the implementation of an organized framework for project portfolio selection through a decision support system (DSS), which they call Project Analysis and Selection System (PASS).

In order to select the optimal mix of R&D projects, the evaluation of each R&D project is important. Traditionally, discounted cash flow (DCF) models are the most frequently used methods for valuation of R&D projects. However, in the field of R&D projects, where high uncertainty and risks are prominent, these methods lose a large amount of their effectiveness. In fact, they fail to assess the real value of these projects which results, among other things, from the flexibility possessed by the management and from the several opportunities these kinds of investment offer. So, in recent years, the real options methods have gained growing attention in R&D project evaluation.

The basic idea of the real options approach is to transfer the sophisticated options pricing models used in capital market theory to the valuation of risky R&D projects.

The real options approach has received great attention in recent years, because an initial investment of an R&D project is similar to the purchase of an option on a future investment. An R&D project usually involves several phases, and the decision makers have the option to stop or defer the project at the end of each phase. In particular, every drug in a pharmaceutical pipeline undergoes sequential phases, following the drug discovery process in which the drug lead is identified, optimized and tested in animals, the drug candidate is taken through three phases of clinical testing: phases I, II and III aims at testing efficacy and safety in sample of healthy volunteers or patients. If the drug succeeds in all three clinical phases a new drug application (NDA) is submitted to approval of FDA; approval allows to launch the drug and commercialize it (Rogers *et al*., 2002).Therefore, each phase is an option that is contingent on the earlier exercise of other options. If the project is a technical success, it creates the option to make a significantly larger investment in the continuing project with relatively higher expected net benefit. If the project fails to achieve the technical success, there is no need to commit any further resources, and therefore the downside risk is limited to the initial investment cost of the R&D project (Wang and Hwang, 2007).

Biopharmaceutical R&D process is a stepped process that can benefit from the adoption of ROA because ROA allows the uncertainty and the flexibility inherent in the process itself to be modelled (Vanhaverbeke *et al*., 2008).

2.1 Real Options optimal portfolio selection

As above mentioned, according to several authors it is better to evaluate the entire R&D project portfolio of a company instead of its single projects, in order to consider the relations and the interdependences between them. These interdependences, ignored if projects are evaluated one by one, usually deal with limited resources consumption, risk balancing and company strategies. A great contribution in this field to scientific literature was brought by Rogers *et al*. (2002) who developed a stochastic optimization model, called OptFolio, able to identify the most valuable projects among the entire R&D project portfolio of a company. The aim of this model is to determine the optimal drug developmental portfolio that maximizes real options value (ROV), overall value of the portfolio, given a set of candidate drugs in various stages of development, estimates of the probability of clinical success, duration, investment required for the remaining stages and forecasts for future market incomes. Despite being particularly close to reality, implementation and use of OptFolio turn out to be very complex. As a matter of fact, a pharmaceutical company may find it hard to set its optimal project portfolio solving a problem with hundreds of constraints and several dozen thousands of variables, with only 20 candidate drugs.

Moreover, OI provides an invaluable tool to balance an innovation portfolio and share risk; in the meanwhile an actively managed portfolio demands judgments calls. The judgments may well be based on quantitative values and careful measurements but the shadow of false positive and false negative judgment persists (Bingham and Spradlin, 2011) and can be mitigated adopting evaluation method able to overcome the underrated problem inherent in the NPV based evaluation method such as the ROA.

Rogers *et al.* (2005) proposed a Real Option mathematical model to select the best licensing strategy for each product in the R&D portfolio. Lo Nigro *et al*. (2012) developed a mathematical model based on ROA to select a R&D optimal portfolio and the best way to develop each of the chosen products following a closed or open innovation path, i.e. developing the product in house or through an alliance with a biotech firm (licensing in the drug).

OI is an incentive to integrate technology management and innovation management (Licthnthaler, 2011) and it reinforces the need to evaluate the entire portfolio of R&D project rather than a stand-alone project.

Blau *et al*. 2004 dealt with our research goal and propose a DSS to manage a portfolio of interdependent new candidate products in the pharmaceutical industry, and even if they acknowledge the suitability of ROA to evaluate the products in the R&D pipeline, they complain the lack, in literature, of ROA based models able to evaluate the entire portfolio and to take into account the interdependencies among the products. Actually, an easy to implement model with these characteristics is now available in literature (Lo Nigro *et al*. 2012), so we will refer to it to built our DSS.

This research aims at developing a DSS for pharmaceutical R&D managers that uses, to evaluate each candidate product, the most promising technique (ROA) with a portfolio perspective, integrating the three categories in which Dickinson *et al.* (2001) classified R&D projects selection models, to check the influence of each input parameter on the optimal solution. The research goal is twofold: firstly to fill in the above highlights literature gap about Real Option based DSS for R&D portfolio selection and secondary to suggest a general structure for DSS able to support selection process.

3 Methodology and numerical example

The paper object is to assess a method to build a heuristic DSS for a R&D portfolio selection. We refer to the proposed model and the numerical example used in Lo Nigro *et al*. (2012): besides, the model, while suggesting the optimal R&D portfolio, is also able to design the financial aspect of the alliance (the payments and the royalty the pharma firm should pour to the biotech one),in order to make the licence attractive for the biotech firm if compared with the alternative to bring the product to the market alone without alliance: the financial side depends on the value added to the product value by the biotech (γ_i') and by the alliance between the pharma and the biotech (γ_i). The numerical example developed Rogers *et al*. (2002) and in Lo Nigro *et al*. (2012) considers 20 candidate products: table 1 shows for each product (P) the type, the impending phase and the involved input parameters (V_0, i.e. the underlying of the call option that evaluates the product and is represented by the NPV of the cash flows coming from the product commercialisation, σ_i, the cash flows volatility, and γ_i -γ_i' above described; for the complete data set of the numerical example please refer to Lo Nigro *et al*., 2012).

Table 1 Input parameters for the base solution

P	*Type*	*Impending phase*	V_{0i} *(M$)*	σ_i	γ_i	γ_i'
1	1		50	80%	1,8	1,3
2	1		100	70%	1,8	1,3
3	1	Phase I	200	50%	2	1,5
4	1		200	60%	2	1,5
5	1		600	50%	2	1,5
6	1		100	20%	1,4	1
7	2		80	50%	1,3	1
8	2		100	70%	1,7	1,2
9	2	Phase II	180	55%	1,9	1,4
10	2		380	35%	1,9	1,4
11	2		80	45%	1,5	1,1
12	3		100	80%	1,2	1
13	3	1st year Phase III	400	30%	1,7	1,3
14	3		700	40%	1,6	1,3
15	4	2nd year	500	35%	1,4	1,2
16	4	Phase III	300	100%	1,2	1,1
17	5	1st year	350			
18	5	FDA Approv.	550			
19	6	2nd year	800			
20	6	FDA Approv.	1150			

The proposed methodology to build up the DSS is driven by the problems that managers are called to answer during the selection process of a R&D portfolio.
The considered mathematical model refers to a complex decision and it is made harder to tackle with because of the evaluation method chosen: the ROA.

In particular, for the numerical example at hand, managers should be interested in understanding how much robust is the obtained solution for the considered input data (the last four columns of table 1).
The relationship between each of these parameters and the selected portfolio is not a linear one because the impact of each parameter on the objective function is not a linear one. To some extent we can refer to the influence of real options parameters to the call value: the so called Greeks and in particular Delta, Δ, that measures the rate of change of option value with respect to changes in the underlying asset's price (Gaardner, 2007). but the model is a constrained optimization one: i.e. the interdependencies among the products play a fundamental role.
So, a sensitivity analysis, in its classical version, is not the best way to understand what could happen to the best solution if the input parameters would be changed.

4 The proposed DSS

The proposed DSS has been built in three steps that cover the three portfolio selection model classes suggested by Dickinson *et al*. (2001).

STEP 1: Mathematical Programming

In order to become more familiar with the model optimization logic, we built a design of experiments to test how, varying the input parameters, the optimal portfolio changes. We vary the input parameters in the range proposed in the numerical example: for each drug's type (type1-type6) we individuate the minimum and maximum value of the input parameters considered (V_0, γ_i -γ_i' , σ_i) and consequently we obtained 104 experiments (for products 17-20, that are in the last phase of development, the evaluation method used is the NPV, so that γ_i -γ_i' and σ_i are not relevant).
We run the optimisation model for the experiments listed in table 2. We analysed the results in order to obtain useful insights for managerial decisions; our considerations are formulated comparing the optimal solution, obtained with the parameters set of table 1 (that from now on, it will be called base solution and consists in a portfolio of 10 products: six to be developed licensing in them, 3,5,6,9,10 and 11, and 5 to be developed in house, namely products 14,15,16 and 19) to the optimal solutions of each of the 104 experiments.

STEP 2 Screening and Sorting

As there is a high number of products and parameters involved in the problem, it could be useful to individuate the most important products, i.e. the products that are more frequently chosen or that give an important financial contribution to Real Options Value (ROV) of the selected portfolio. Experiments' results highlight as some products belong to many best portfolios and others do not: so we found the "contribution" in terms of ROV of each product to the obtained solutions (without considering the possibility offered by some products to finance other products) and then we sorted the products out basing on this value (i.e contribution). In this way we can implement the Pareto analysis and individuate products that mostly contribute to the best solution: we can notice that P19-P15-P5-P14 (class A) account for the 66% of the overall ROVs, P10-P20-P16-P9-P3 (class B) for 29% and the remaining ones (class C) for just 5% We tried a Pareto analysis also on the frequency of each product that is part of optimal portfolios, but in this case, the distribution is quite uniform: so a Pareto analysis is not suitable.

Table 2 Design of experiments

	Var. levels	V_0	σ_i	γ_i-γ_i'
	MIN	E1	E2	E3
P1	MAX	E4	E5	E6
	MIN	E7	E8	E9
P2	MAX	E10	E11	E12
	MIN	E13	E14	E15
P3	MAX	E16	E17	E18
	MIN	E19	E20	E21
P4	MAX	E22	E23	E24
	MIN	E25	E26	E27
P5	MAX	E28	E29	E30
	MIN	E31	E32	E33
P6	MAX	E34	E35	E36
	MIN	E37	E38	E39
P7	MAX	E40	E41	E42
	MIN	E43	E44	E45
P8	MAX	E46	E47	E48
	MIN	E49	E50	E51
P9	MAX	E52	E53	E54
	MIN	E55	E56	E57
P10	MAX	E58	E59	E60
	MIN	E61	E62	E63
P11	MAX	E64	E65	E66
	MIN	E67	E68	E69
P12	MAX	E70	E71	E72
	MIN	E73	E74	E75
P13	MAX	E76	E77	E78
	MIN	E79	E80	E81
P14	MAX	E82	E83	E84
	MIN	E85	E86	E87
P15	MAX	E88	E89	E90
	MIN	E91	E92	E93
P16	MAX	E94	E95	E96
	MIN	E97		
P17	MAX	E98		
	MIN	E99		
P18	MAX	E100		
	MIN	E101		
P19	MAX	E102		
	MIN	E103		
P20	MAX	E104		

The Pareto analysis on the product's contribution to the value of optimal portfolios allows to focus the attention **on** the products that have an important weight in the overall

obtained optimal portfolios. This screening task is useful to concentrate the effort of time consuming deeper analyses on products belonging to class A.

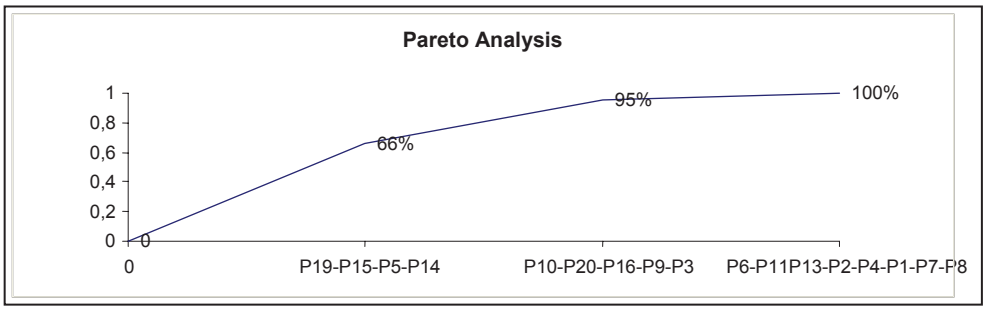

Figure 1 Pareto analysis of the product portfolio value contribution.

STEP THREE *What if* rules and Mapping

It is also interesting to understand the impact of each parameter to the optimal portfolio: in particular we can distinguish between direct effect and secondary effect. We refer to direct effect to indicate the impact the product *i* parameter has on the product *i* itself and we refer to secondary effect to indicate its impact on the 19 remaining drugs: for example in E4 (table 2) the parameter changed is V_0 for the product 1 that is equal to the maximum of the V_0 for the type 1's products (V_0=600) and it can influence either product 1 choice (direct effect) or P2-P19 choice (secondary effect).
The obtained optimal solution for E4 suggests to develop in house P1-P15-P16 and P19 and to licensing-in P2-P5-P9-P10-P11-P13.
We can observe that, comparing this solution to the base one, a higher V_0 for product 1 has a direct consequence on product 1 that is chosen to be developed in house and secondary effect on other products (product 3, 6 and 14 don't belong no more to the best portfolio while products 2 and 13 are chosen)**:** it is a kind of substitution effect (Pindyck and Rubinfeld, 2008). The secondary effects are very hard to understand, but to this purpose, the above proposed Pareto analysis combined with the *what if* rules (below proposed) , could be helpful.
A direct effect analysis on the products of the base solution, that belong to class A and class B of the Pareto analysis, allows to gain some insights.
In particular we can observe for P15 (E85 and E88) for higher values of V_0 the model suggests to develop it in house, while for the minimum value to licence in it; for P3 (E13 and E16) for the lowest value of V_0 the model suggests do not to include it in the optimal portfolio, otherwise to licence-in it.
Looking at the solutions obtained for E25 and E28 (P5), E31 and E34 (P6), E55 and E58 (P10), E91 and E94 (P16), E101 and E102 (P19) no direct effect can be observed and then the base solution is robust.
These considerations allow to formulate the following what if rule:

> *Rule 1 The higher the value of V0 the higher the opportunity to select the drug and to develop it in house.*

This is an expected result that agree with the influence of the underlying (V_0) on the call value as foreseen by Δ: the higher the value of V_0 of a product, the higher its real option value.

As far as γ_i -γ_i' are concerned a lower value of γ_i -γ_i' (for P3, P6, P9, P10 and P11) causes the exclusion of the product from the optimal portfolio or the suggestion to develop it in house (P5 and P10).
This is another expected result, because the licensing-in is a convenient solution to develop a product if the alliance adds value to the product: moreover the analysis suggests that P5 and P10 are valuable products to maintain in the portfolio and to: develop in house, if licensing is not a convenient alternative (low value for γ_i -γ_i'); the other products are no more in the optimal portfolio if the licensing solution is not convenient any more.
These considerations allow to formulate the following what if rule:

> *Rule 2 The higher the value of* γ_i -γ_i'*the higher the opportunity to select licensable drugs and to licence-in them:*

The influence of σ_i is limited to two cases: we can conclude that, in the considered example, the base solution is robust if σ_i varies.
The results can also give interesting suggestions on the portfolio mix: figure 2 shows a 4 quadrants bubble chart; the four quadrants are obtained combining two variables with two levels each: quadrant 1 refers to products of type 1 or 2 developed in alliance, quadrant 2 refers to products of type 3, 4, 5 or 6 developed in alliance; quadrant 3 refers to products of type 3, 4, 5 or 6 developed in house and finally, quadrant 4, refers to products of type 1 or 2 developed in house. For each quadrant the axes are respectively the average contribution of the product to the overall optimal solutions obtained for experiments listed in table 2 and the times the product appears in the optimal solutions of the same experiments: for example in quadrant 4 each bubble refers to a product *i* of type 1 or type 2 and to the optimal solutions in which it is developed in house ($HOSs_i$), the bubble is centred according to the average contribution of the product *i* to its $HOSs_i$ and to the number of $HOSs_i$ for the considered product and its area is proportional to the overall contribution of product *i* to the optimal considered solutions ($HOSs_i$).
As shown in figure 2 (Q1) type 1 e type 2 products, which have the impending phase in the first ones considered in the numerical example, when selected, are developed licensing in them; while type 3, 4, 5 and 6 products, if selected, are developed in house (quadrant3) (Bianchi *et al*., 2011). Some exceptions are represented by P13 (Q2) that is of type 3 and, if selected, is developed in alliance (instead of in house) and by P1, P10 (Q4) and P15 (Q2) that, for just 1 experiment, are selected and developed in the opposite expected way: P13 goes into the optimal portfolios because of secondary effects, while P1 is developed in house when its V_0 assumes the highest value; P10 when γ_i -γ_i' achieve the lowest value and then the alliance is not a promising alternative, P15 is developed in alliance when its V_0 is equal to the minimum value (direct effect). Moreover, figure 2 gives an alternative graphical representation of the Pareto analysis according to the mapping methods.

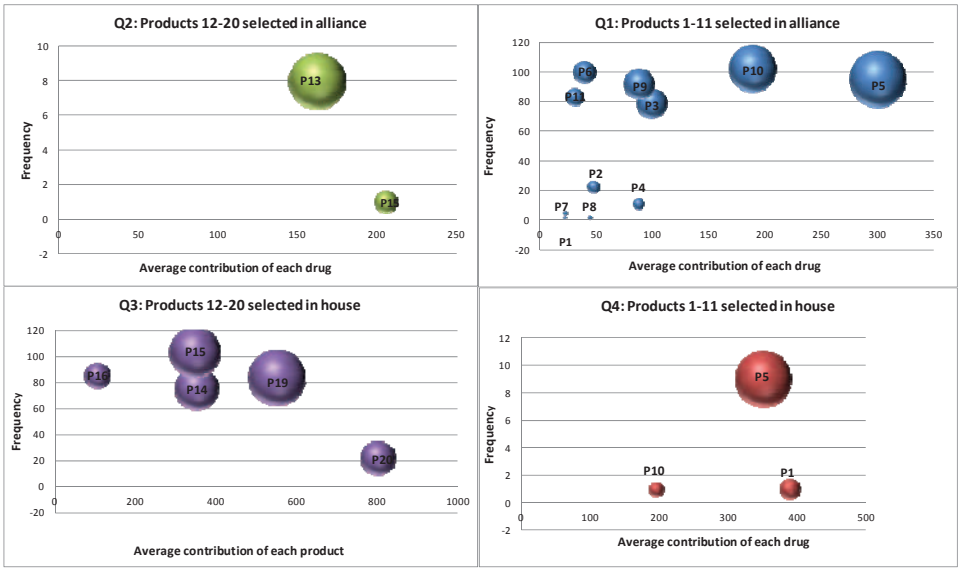

Figure 2 Selected products map.

5 Conclusions

The paper aims at supporting managers in Innovation Management in the pharmaceutical industry, in particular during the selection process of the R&D candidate products to develop. This is a constrained problem, limited resources cannot allow to develop all the potential candidates and it obliges to adopt a portfolio perspective; moreover some R&D processes have characteristics that require advanced evaluation methods like ROA. Literature offers mathematical models to tackle with the selection process in the depicted scenario (Real Option base R&D evaluation of interdependent projects). We propose a DSS articulated in three steps that is able to: design an experimental plan to test the influence of uncertain parameters of the input data set on the optimal solution, analyse the obtained results from the experimental plans in order to obtain *what if* rules and map the results in an effective way. Moreover the suggested *what if* rules confirm theoretical knowledge about ROA and OI: the first rule confirms the importance of the underlying value of the real option of each candidate product in selecting the product itself, while the second one confirms the importance of complementary resources in OI.

Research findings show interesting managerial and academic implications: the main driver in product robustness (resilience in the optimal portfolio) and in determining the way the product is developed (in house or licensing it) is the net present value of cash flows coming from the commercialization of the drug (that represents the underlying of the related call option); the added value from the potential partners, expressed by $\gamma_i - \gamma_i'$, plays an important role in products selection, too.

The proposed methodology offers general guidelines to built a DSS that can be applied to mathematical programming with goal similar to the one we dealt with.

Further developments aim at investigating the diversification side of the problem and then at obtaining a risk-return efficient frontier: in order to accomplish this task correlation between each couple of products should be known. This is an interesting task because, as demonstrated in van Bekkum *et al*. (2009), correlation among R&D products

with Real Options characteristics act differently than usually and in particular negative correlation only slightly reduces portfolio risk.
.Moreover a fuzzy version of the mathematical model, and then of the DSS, could properly tackle with the uncertainty of the involved parameters.

References

Aaker , D.A. and Tyebjee, T.T. (1978) A model for the selection of interdependence projects. IEEE Transactions On Engineering Management, EM- 25, 2, 30-36.

Baker, N., Freeland, J., (1975). Recent advances in R&D benefit measurement and project selection methods. Management Science 21, 1164–1175

Baker, N.R., (1974). R&D project selection model: An assessment. IEEE Transactions on Engineering Management EM-21, 165–171.

Beaujon, G.J., Marin, S.P., McDonald, G.C.(2001). Balancing and optimizing a portfolio of R&D projects. Naval Research Logistics 48, 18–40.

Bianchi, M., Cavaliere, A., Chiaroni, D., Frattini, F. and Chiesa, V., (2011). Organisational modes for Open Innovation in the bio-pharmaceutical industry: An exploratory analysis. Technovation

Bingham, A., Spradlin, D., 2011. The Open Innovation Marketplace: Creating Value in the Challenge Driven Enterprise, FT Press.

Blau, G., E., Pekny, J., F., Varma, V., A. and Bunch, P. R. (2004) Managing a Portfolio of Interdependent New Product Candidates in the Pharmaceutical Industry. The Journal of Product Innovation Mangement 2004; 21: 227-245

Chien, C.(2002). A portoflio- evalutation framework for selecting R&D projects,R&D Management, 32,4

Chu, P., V., Hsu, Y. and Fehiling, M. (1996) A decision support system for project portfolio selection. Computer in industry.

Cooper, W.W., Li, S., Seiford, L.M., Tone, K., Thrall, R.M., Zhu, J., (2001). Sensitivity and stability analysis in DEA: Some recent developments. Journal of Productivity Analysis 15, 217–246

Danila, N., (1989). Strategic evaluation and selection of R&D projects. R&D Management 19, 47–62.

Dickinson, Michael W., Thornton, Anna C. and Graves Stephen. (2001). Technology Portfolio Management: Optimizing Interdependent Projects Over Multiple Time Periods. IEEE transactions on engineering management, vol. 48, no. 4

Eilat H. , Golany ,B. , Shtub, A.(2006). Constructing and evaluating balanced portfolios of R&D projects with interactions: A DEA based methodology . European Journal of Operational Research 172 1018–1039

Farrukh, C., Phaal, R., Probert, D., Gregory, M., Wright, J., (2000). Developing a process for relative valuation of R&D programmes. R&D Management 30 (1), 43–53.

Fox, G.E. , Baker, N.R and Bryant, J. L(1984) Economics models for R&D project selection in the presence of project interactions. Management Science, 30, 890-902.

Gaardner Haug, Espen (2007). The Complete Guide to Option Pricing Formulas. McGraw-Hill Professional. ISBN 0-07-138997-0, 9780071389976

Gear, T.E. and Cowie, G.C. (1980) A note on modeling project interdependence in research and development. Decision Science. II, 738- 748.

Ghasemzadeh, F. and Archer, N.P (2002) .Project portfolio selection through decision support. Decision support system 2000 F.

Goldfarb, D. and Iyengar, G. (2003) Robust Portfolio selection problems. Mathematics of Operations research, Vol. 28 n 1, pp 1-38

Hall, D.L., Nauda, A. (1990). An interactive approach for selecting R&D projects. IEEE Transactions on Engineering Management 37,126–133.

Hartmann, M. and Hassan, A. (2006). Application of real options analysis for pharmaceutical R&D project valuation-Empirical results from a survey. Research Policy Vol. 35, 343-354.

Henriksen, A. D. and Traynor, A. J.,(1999). A Practical R&D Project-Selection Scoring Tool. IEEE Trans. On Eng. Manag. , vol. 46, no.2.

Keeney R.L. (1987) An analysis of the portfolio of sites to characterize for selecting a nuclear repository. Risk Analysis, 7, 195-216.

Liberatore, M.J., (1988). A decision support system linking research and development projects selection with business strategy. Project Management Journal 9 (5), 14–21.

Liberatore, M.J., Titus, G.J.(1983). The practice of management science in R&D project management. Management Science 29, 962–975.

Licthnthaler, U., (2011). Open Innovation: Past Research, Current Debates and Future Directions. Academy of Management Perspective, 75-93.

Lo Nigro, G, Enea, G., Morreale A., (2012). Real Option Analysis Opens Innovation: the biopharmaceutical Case, Proceedings of the 17th International Working Seminar on Production Economics, Editors Grubbström, R., W. And Hinteruhuber, H., Innsbruck February 20-24, 2012

Loch, C.H., Pich, M.T., Terwiesch, C., Urbschat, M. (2001). Selecting R&D projects at BMW: A case study of adopting mathematical programming models. IEEE Transactions On Engineering Management 48 (1), 70–80.

Markowitz, H.M.(1952). Portfolio selection, J. Finance 7, pp. 77–91.

McGrath, R.G., Ferrier W.J. and Mendelow A.L. (2004). Real options as engines of choice and heterogeneity. Academy of Management Review 2004, Vol. 29, No. 1, 86–101.

Perlitz, M., Peske, T., Schrank, R. (1999). Real options valuation: the new frontier in R&D project evaluation? R&D Management Vol. 29, Issue 3: 255–270

PhRMA (2011). Pharmaceutical industry profile 2010.

Pindyck, Robert, S. and. Rubinfeld , Daniel, L.,(2008) .Microeconomics (7th Edition)

Rogers, M. J., and Maranas, C. D., (2005). Valuation and design of pharmaceutical R&D licensing deals. AIChE Journal January Vol. 51, No. 1,198-209.

Rogers, M. J., Gupta, Maranas, C. D., (2002). Real options based analysis of optimal pharmaceutical research and development portfolios. Ind. Eng. Chem. Res. 41, 6607-6620

Schmidt, R.L., Freeland, J.R., (1992). Recent progress in modeling R&D project-selection processes. IEEE Transactions on Engineering Management 39, 189–201.

Souder W.E and Mandakovic, T.(1986). R&D project selection models. Research Management, 29, 36-42.

Vanhaverbeke, W., Van de Vrande, V., Chesbrough, H., (2008). Understanding the Advantages of Open Innovation Practices in Corporate Venturing in Terms of Real Options. . Vol. 17, (251-258).

Van Bekkum, S., Pennings, E. And Smith, H., (2009), A real options perspective on R&D portfolio diversification, Research Policy, 38 (2009), 1150-1158

Wang, J. and Hwang, W.L., (2007). A fuzzy set approach for R&D portfolio selection using a real options valuation model. Omega, Vol. 35, Issue 3 (247-257).

Weingarten, H.M. (1966). Capital budgeting of interrelated projects: survey and synthesis. Management Science. 12,485-516.