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A Source-Sink Model for Optimum Allocation of Technology Innovation Portfolios

Raymond R. Tan[a], Kathleen B. Aviso[a,*], Denny K. S. Ng[b]

[a]Chemical Engineering Department, De La Salle University, 2401 Taft Avenue, 0922 Manila, Philippines
[b]Department of Chemical and Environmental Engineering/Centre of Sustainable Palm Oil Research (CESPOR), University of Nottingham Malaysia Campus, Jalan Broga, 43500 Semenyih, Selangor, Malaysia
kathleen.aviso@dlsu.edu.ph

Commercialization of emerging green technologies is essential to improving the sustainability of industrial processes. In practice, it is necessary to match funding sources (e.g., research and development grants, venture capital, etc.) with projects at different maturity levels. Because of inherent uncertainties that characterize and evaluate new technologies, the decision-making process is typically fraught with risk, which can be mitigated with the use of systematic decision support methods. In this work, an optimization model is developed for optimal allocation of funds to a portfolio of innovation projects based on the available funds and different levels of technology maturity. The model is based on source-sink formulation typically used in process integration applications. Each source is a fund of known size and can only be used for projects of a specified minimum return on investment (ROI) and minimum technological readiness level (TRL); each project has an estimated cost, TRL and an ROI range across techno-economic risk scenarios. The model is formulated as a bi-objective mixed integer linear programming (MILP) model, using the conservative and optimistic total portfolio ROI as dual objective functions. The methodology is demonstrated using a pedagogical case study.

1. Introduction

The development of new technologies is similar to a portfolio management problem (Cooper and Edgett, 2001). The general problem is complex due to temporal aspects and interdependencies among projects (Dickinson et al., 2001). In practice, the presence of multiple criteria (Morcos, 2007) and uncertainties in performance level (Aviso et al., 2017) further complicate decision-making. In practice, success rates are thus rather low (Li et al., 2015). Research opportunities in technology portfolio management are described in detail by Meifort (2016). Technology Business Incubators (TBI) are entities established via tripartite partnerships involving academia, industry and government, which are intended to facilitate the emergence of Technology-Based Firms (TBFs) which rely on newly developed technology for the creation of new businesses (Mian et al., 2016).

In practice, TBIs face the challenge of prioritizing technologies in their portfolio. These technologies compete for limited financial resources, which need to be allocated based on the expected benefits to investors. In addition to conventional financial metrics, the presence of new technologies has to be accounted for by TBI managers. Maturity of new technologies is often gauged using the well-established Technology Readiness Level (TRL) metric developed in the 1960s by the United States of America National Aeronautics and Space Administration (NASA) (Mankins, 2009). TRL uses a 9-point scale to rate technologies, as shown in Table 1. The TRL concept has been applied to the assessment of different sustainable technologies, such as negative emission technologies (McLaren, 2012), composite materials recycling technologies (Rybicka et al., 2016), and battery electric vehicle technologies (Andwari et al., 2017), among numerous others. Different modifications and extensions have also been proposed for the basic TRL concept. For example, Straub (2015) proposed a new TRL score of 10 to indicate extensive commercial experience with a mature technology. An analogous System Readiness Level (SRL) was proposed to account for interactions or interdependency in multi-component systems (Lemos and Chagas, 2016).

Table 1: The NASA TRL scale (Mankins, 2009)

TRL	Description
1	Basic principles observed and reported
2	Technology concept and/or application formulated
3	Analytical and experimental critical function and/or characteristic proof of concept
4	Component validation in a laboratory environment
5	Component validation in a relevant environment
6	System/subsystem model or prototype demonstration in a relevant environment
7	System prototype demonstration in an operational environment
8	Actual system completed and qualified through test and demonstration
9	Actual system proven through successful mission operations

Process Integration (PI) originally emerged as a systematic framework for thermal energy recovery in process plants. During the course of multiple decades of development and application, PI has diversified to address more general problems in industrial efficiency and sustainability, as documented in a definitive handbook containing many of the most significant contributions in this area (Klemeš, 2013). Similarly, scientific conferences have shaped the evolution of PI in recent years (Klemeš et al., 2017). The most important methodologies in PI are Pinch Analysis (PA) and Mathematical Programming (MP), which provide complementary problem-solving strategies based on their respective strengths and drawbacks. PA is a powerful approach to problem analysis and decomposition and provides insights that facilitate interpretation and communication; it has also been shown to be applicable to various non-conventional PI problems involving allocation of streams with measurable quality aspects (Tan et al., 2015). The earliest application of PA to support financial decisions was first proposed by Zhelev (2005). Bandyopadhyay et al. (2016) proposed a graphical approach for allocating funds from multiple sources to multiple projects with different levels of expected return on investment (ROI). This procedure was based on the Material Recovery Pinch Diagram (MRPD), whose applicability to a broad range of PI problems is described in greater detail by Foo (2012). Roychaudhuri et al. (2017) extended this graphical method and demonstrated its applicability to funding industrial energy conservation projects. A mixed integer linear programming (MILP) model based on these previous developments was proposed recently by Roychaudhuri and Bandyopadhyay (2018).

In this paper, a bi-objective MILP model is developed for allocating financial resources from multiple funds (sources) to multiple innovation projects (sinks). For both sources and sinks, quality restrictions are defined by ROI and TRL. The rest of the paper is organized as follows. A formal problem statement is given in Section 2. The model formulation is given in Section 3 and is applied to a representative case study in Section 4. Conclusions and further prospects for research are given in Section 5.

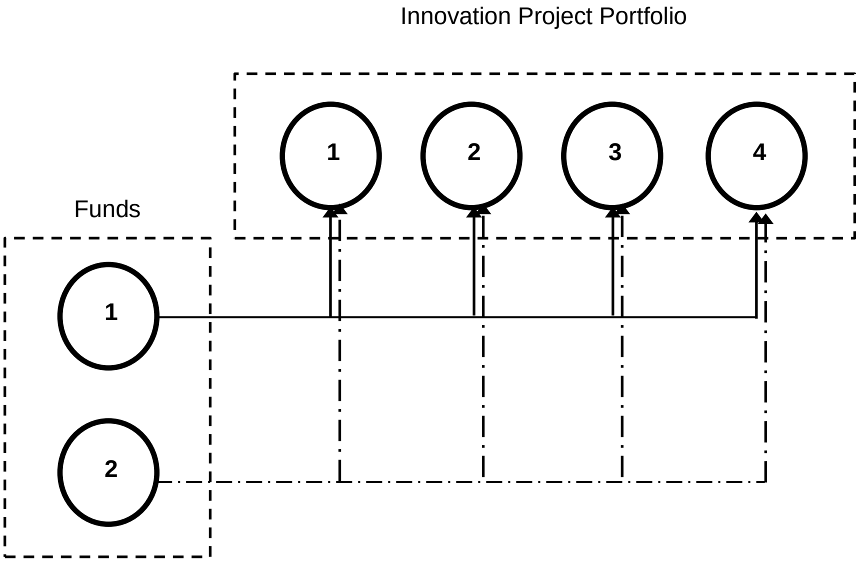

Figure 1: Superstructure for the fund allocation problem

2. Formal problem statement

For this problem, the corresponding superstructure is shown in Figure 1. The formal problem is as follows:

- Given M funds (sources), each with a defined size, as well as a minimum TRL and ROI requirement;
- Given N independent innovation projects (sinks), each with a defined funding requirement, as well as TRL and lower/upper bounds for ROI;
- The problem is to allocate financial resources from the M funds to the N sinks in order to achieve the best ROI, while ensuring that the TRL and ROI restrictions are met.

3. Model formulation

The bi-objective MILP model is formulated as follows:

$$\max \Sigma_j \, ROI_j^U P_j b_j \quad (1)$$

$$\max \Sigma_j \, ROI_j^L P_j b_j \quad (2)$$

subject to:

$$\Sigma_j \, r_{ij} \leq F_i \qquad \forall i \quad (3)$$

$$\Sigma_i \, r_{ij} = P_j b_j \qquad \forall j \quad (4)$$

$$\Sigma_j \, ROI_j^L r_{ij} \geq FROI_i \, \Sigma_j \, r_{ij} \qquad \forall i \quad (5)$$

$$r_{ij} \leq M \, b_{ij} \qquad \forall i, j \quad (6)$$

$$b_{ij} \in \{0, 1\} \qquad \forall i, j \quad (7)$$

$$b_{ij} \leq (TRL_j / FTRL_i) \qquad \forall i, j \quad (8)$$

$$b_j \in \{0, 1\} \qquad \forall j \quad (9)$$

where the model parameters are as follows: ROI_i^U is the optimistic estimate of ROI of project i; ROI_i^L is the pessimistic estimate of ROI of project i; F_i is the size of fund i; P_j is the cost of project j; $FROI_i$ is the minimum ROI threshold for the use of fund i; M is an arbitrary large number; TRL_j is the TRL of project j; $FTRL_i$ is the minimum TRL threshold of fund i; and the model variables are as follows: r_{ij} is the allocation of financial resources from fund i to project j; b_j is the binary decision whether or not to fund project j; and b_{ij} is the binary decision whether or not to allocate financial resources from fund i to project j.

The objective functions are to maximize the optimistic and pessimistic portfolio ROIs (Eq(1) and Eq(2)). These objectives represent attitudes of risk-seeking and risk-averse decision makers, and the use of distinct objective functions is based on the Partitioned Multi-objective Risk Method (PMRM), which treats different levels of risk separately to ensure that information on probability extremes are not lost in the decision-making process (Santos and Haimes, 2004). Eq(3) ensures that the total utilization of any given fund does not exceed its size, while Eq(4) ensures that the allocated funds are sufficient to meet the cost of any selected project. The average pessimistic ROI for all projects supported by any given fund should be at least equal to its specified minimum ROI threshold (Eq(5)). Eq(6) and Eq(7) relate each flow of financial resource to a corresponding binary variable, while Eq(8) ensures that allocations are only allowed when the project TRL exceeds the fund's TRL minimum threshold. The TRL constraint may be visualized as in a manner similar to the "staircase" composite curves proposed for water integration problems by Dhole et al. (1996). Eq(9) defines the binary variable for project selection. The MILP model can be easily solved to global optimality using commercial software such as LINGO. To deal with the two objective functions, the Pareto front can be traced using the ε-constraint method.

4. Illustrative case study

This case study focuses on new technologies for processing residual biomass from the palm oil industry. This agro-industrial sector is an important part of the economy of many developing countries, particularly leading producers such as Malaysia and Indonesia in Southeast Asia. Utilization of the abundant residual biomass from palm oil mills offers the potential of creating further economic growth, while also improving the sustainability

profile of the entire industry (Ng et al., 2012). However, doing so will require the development and commercial deployment of biomass processing and utilization technologies.
A hypothetical but plausible scenario is presented here with funding sources as shown in Table 2, and projects as shown in Table 3. The ROI values are given in terms of cumulative returns over project lives of 20 y. Note from this data that the TRL levels are related to the gap between the optimistic and pessimistic ROI estimates. For mature technologies, ROI can be predicted more precisely, while for less mature ones, there is greater degree of uncertainty and the potential to fund less mature technologies is reduced by risk aversion among the managers of the different funds.

Table 2: Fund data for case study

Fund type	Available amount (USD)	Minimum TRL threshold	Minimum ROI threshold (%)
Government grant	8,000,000	4	20
Industry funding	10,000,000	7	125
Crowd funding	6,000,000	6	130
Angel investor funding	2,000,000	6	135

Table 3: Project data for case study

Project	Cost (USD)	TRL	Optimistic ROI (%)	Pessimistic ROI (%)
Integrated biogas and wastewater treatment system	6,250,000	5	140	125
Biomass-fired power plant	5,500,000	8	150	120
Dried long fiber plant	1,500,000	9	220	200
Biofertilizer plant	3,750,000	9	370	330
Palm pellet plant	2,000,000	9	200	180
Biochemical process plant	7,500,000	4	180	100

Solving the bi-objective MILP model using the ε-constraint method gives two Pareto-optimal solutions shown in Figure 2 that correspond to the maximization of the optimistic and pessimistic ROIs. Optimizing the model based on Eq(1) gives an optimal optimistic ROI of USD 42.925 M, with the funding allocation as shown in Table 4. For this solution, the pessimistic ROI is USD 33.075 M. This value represents the worst-case result for an optimistic decision-maker. On the other hand, optimizing the model based on Eq(2) gives an optimal pessimistic ROI of USD 33.388 M, for which the funding allocation is shown in Table 5. The corresponding optimistic (best-case) ROI for this solution is USD 38.175 M.

Table 4: Funding allocation in USD based on optimistic ROI

Project	Government grant	Industry funding	Crowd funding	Angel investor funding
Integrated biogas and wastewater treatment system				
Biomass-fired power plant		3,000,000	2,500,000	
Dried long fiber plant			1,500,000	
Biofertilizer plant		1,750,000		2,000,000
Palm pellet plant			2,000,0000	
Biochemical process plant	7,500,000			

Table 5: Funding allocation in USD based on pessimistic ROI

Project	Government grant	Industry funding	Crowd funding	Angel investor funding
Integrated biogas and wastewater treatment system	6,250,000			
Biomass-fired power plant		3,000,000	2,500,000	
Dried long fibber plant			1,500,000	
Biofertilizer plant		1,750,000		2,000,000
Palm pellet plant			2,000,0000	
Biochemical process plant				

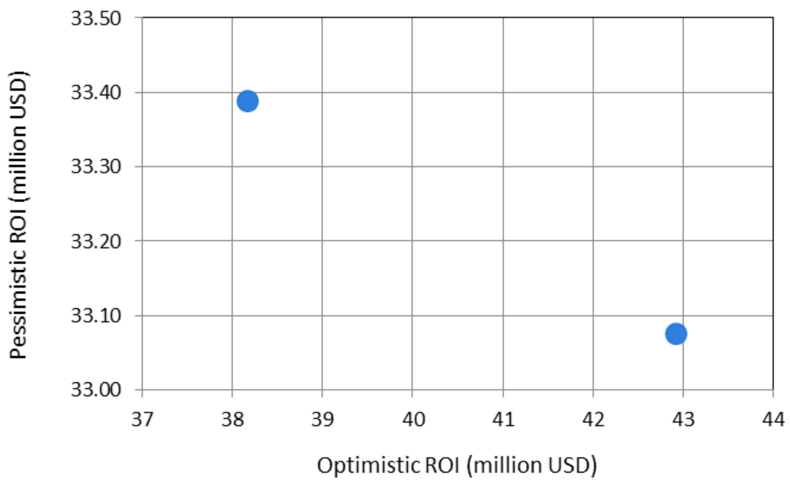

Figure 2: Pareto optimal solutions to the case study

Comparison of the two solutions shows that four projects (i.e., the biomass-fired power plant, dried long fibber plant, biofertilizer plant, and palm pellet plant) are all funded in the same manner via industry funding, crowd funding and angel investor funding. The two solutions differ only in the allocation of the government grant to either the first project (the integrated biogas and wastewater treatment system) or the sixth one (the biochemical process plant). Both of these projects do not have sufficiently high TRL to be supported by the other funding schemes. However, due to the grant limitations, it is not possible for these two relatively immature projects to be funded simultaneously, so the model is forced to select one of them for implementation. Depending on the degree of risk aversion of the TBI manager, the fund may be allocated to maximize either the best-case or worst-case solution. The risk-averse solution ensures a pessimistic ROI that is guaranteed to be USD 0.313 million higher than the alternative; however, this result comes at the expense of the optimistic ROI being USD 4.75 million less than is possible from a more risk-tolerant attitude.

5. Conclusions

A source-sink model has been developed for the optimal allocation of financial resources to fund the development of a technology portfolio. The model formulation is based on source-sink models used extensively in PI applications for resource conservation problems; it also considers TRL and inherent uncertainties in ROI. A case study on biomass processing technologies is used to illustrate the practical application of the model for providing decision support for innovation management. The model itself is static and does not account for interactions among the technology options; more detailed restrictions on fund use are also not considered here. Future work can focus on further generalizations of the model to relax these simplifying assumptions. Alternative solution approaches based on other PI tools such as PA or P-graph can also be explored.

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