Optimization Models for Financing Innovations in Green Energy Technologies

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Commercialization of emerging green technologies is essential to improve the sustainability of industrial processes. However, there are risks inherent in funding the development of new technologies that act as a significant barrier to their commercialization. Mathematical models can provide much-needed decision support to allow optimal allocation of funds, while managing the implications of techno-economic risk. The Technology Readiness Level (TRL) scale is a well-established figure of merit approach for quantifying the maturity of stand-alone technologies, while the more recently developed System Readiness Level (SRL) scale is applicable to technology networks with interdependent components. These technology maturity scales are intended mainly to be used for the passive assessment of a given state of technology, but may be incorporated within an optimization model to aid in innovation planning. In this work, two mixed integer linear programming (MILP) models are proposed to optimize strategies for funding innovation. The first model is a bi-objective MILP for optimizing the allocation of funds to a portfolio of independent innovation projects. The model is based on source-sink formulation and uses information on TRL and return on investment (ROI) to determine the best allocation. The second model is a robust MILP that optimizes the allocation of limited project funds in order to maximize the SRL of a system of emerging technologies. This approach accounts for Integration Readiness Level (IRL) among mutually interdependent technologies. Both models are demonstrated with illustrative case studies on biorefinery technologies in order to demonstrate their capabilities.

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List of acronyms

CCS	CO_2 capture and storage
CHP	Combined Heat and Power
EFB	Empty Fruit Bunches
GTL	Gas-to-Liquid
IRL	Integration Readiness Level
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MP	Mathematical Programming
NASA	National Aeronautics and Space Administration
NET	Negative Emission Technologies
OPF	Oil Palm Fronds
PA	Pinch Analysis
PI	Process Integration
PKS	Palm Kernel Shell
PMRM	Partitioned Multi-objective Risk Method
ROI	Return on Investment
SRL	System Readiness Level
TBF	Technology-Based Firms
TBI	Technology Business Incubators
TRL	Technology Readiness Level

1. Introduction

Emerging green technologies will play an important role in improving the sustainability of industrial processes in the future. Many of these new technologies are still in various stages of maturity and will need substantial investment for further development leading to eventual commercial deployment. Empirical results in the literature show the importance of technological innovation in achieving environmental gains. For example, Huang et al. [1] analysed the effect of research and innovation on the energy intensity of China, and concluded that innovation resulting from local research and development was highly influential factor in driving improved economy-wide energy efficiency. Efficient spending on research and development is also a key determinant of corporate competitiveness (Carrillo and Jorge, 2018). Innovation is typically supported by government-funded research grants in the early stages, with progressively greater industry investment as technology matures [2]. Although access to financing is essential to technology commercialization, such financial resources are generally limited, and projects must compete to secure support for development activities [3]. Allocation of funds to develop new technologies can be framed as a portfolio management problem [4]. In practice, the problem is complicated by temporal effects, component interdependencies [5], multiple criteria [6], and uncertainties in performance level [7]. As a result, empirical data also shows that commercialization success rates are low [8]. Meifort [9] discusses research prospects in the area of technology portfolio management. Portfolio diversification provides a means of mitigating some of the techno-economic risks associated with new technologies, for instance in the case of clean electricity generation [10]. In order to improve the odds of successful commercialization, partnerships are often formed involving academia, industry and government, and through the formation of Technology Business Incubators (TBI). The latter are organizations that are meant to utilize new technologies for the creation of new businesses, known as Technology-Based Firms (TBFs) [11]. TBIs maintain technology portfolios at different levels of development and must allocate available financial resources in order to maximize overall success rates. The problem of resource allocation for TBI managers is further compounded by the presence of new technologies that are subject to higher levels of techno-economic risk than mature ones. Quantitative techniques to support critical decisions are thus needed [12]. These methods should take various techno-economic and environmental criteria into consideration [13].

The *Technology Readiness Level* (TRL) is a figure of merit scale originally developed in the 1970s by the National Aeronautics and Space Administration (NASA) of the United States, but which has since become widely used as a measure of maturity of generic technologies [14]. For example, TRL has been adopted in the EU as a general framework for assessing classes of green technologies [15]. TRL makes use of a discrete 9-point scale corresponding to levels of maturity with well-defined descriptions, as shown in Table 1 [14].

Table 1. TRL and IRL 9-point scales.

Level	TRL Definition (Mankins, 2009a)	IRL Definition (Sauser et al., 2008)
1	Basic principles observed and reported.	An interface between technologies has been identified with sufficient detail to allow characterization of the relationship.
2	Technology concept and/or application formulated.	There is some level of specificity to characterize the interaction between technologies through their interface.
3	Analytical and experimental critical function and/or characteristic proof-of-concept.	There is compatibility between technologies to orderly and efficiently integrated and interact.
4	Component and/or breadboard validation in laboratory environment.	There is sufficient detail in the quality and assurance of the integration between technologies.
5	Component and/or breadboard validation in relevant environment.	There is sufficient control between technologies necessary to establish, manage, and terminate the integration.
6	System/subsystem model or prototype demonstration in a relevant environment.	The integrating technologies can accept, translate, and structure information for its intended application.
7	System prototype demonstration in the planned operational environment.	The integration of technologies has been verified and validated with sufficient detail to be actionable.
8	Actual system completed and qualified through test and demonstration in the operational environment.	Mission qualified through test and demonstration in the system environment.
9	Actual system proven through successful system and/or mission operations.	Integration is mission proven through successful mission operations.

In practice, TRL values are judged subjectively based on expert estimates using these criteria. According to Mankins [16] technology maturity is strongly linked to the risk of project failure, and TRL can thus be used as an intrinsic component for risk assessments. It has also been pointed out that technology assessment is an important component of innovative and sustainable process design [17]. There have been attempts to develop TRL evaluation software to facilitate technology assessment [18]. More recently, it has been proposed to incorporate a higher TRL level corresponding to an extended history of proven commercial use of a technology [19]. The TRL metric has been used in recent literature to assess different green technologies, such as negative emission technologies [20], composite material recycling techniques [21], battery electric vehicle technologies [22], plasma-based thermochemical processes [23], CO_2 capture and storage (CCS) technologies [24], CO_2 utilization technologies [25], biorefineries [26], and wave energy systems [27], among others.

One important limitation of TRL is that it only provides an evaluation of a single technology taken in isolation. It cannot be used to account for innovation networks involving multiple interacting or interdependent technologies, which collectively can exhibit emergent dynamic properties [28]. Financing of innovation in such systems is a complex task that needs to account for interactions among components, as well as the probable presence of multiple decision-makers (i.e., firms) [29]. To overcome this limitation, Sauser et al. [30] introduced the *System Readiness Level* (SRL) figure of merit to quantify the maturity of a set of interdependent technologies. SRL is a composite function of the TRL of component technologies as well as the *Integration Readiness Level* (IRL), which measures the pairwise maturity of the interface between two mutually dependent technological components. The SRL and IRL quantify network effects that occur in value chains of interdependent green technologies [25]. Like TRL, the IRL also uses a 9-point scale as shown in Table 1. Note that TRL and IRL definitions for levels 8 and 9 are very similar, but are less so for lower levels of maturity. The computation of SRL from the IRL and the component TRL values is described in a later section of this paper; its value ranges continuously from 0 to 1, and maturity level descriptions are defined in Table 2. The use of TRL and SRL metrics in the literature has mostly been limited to the assessment of current technological state, with a few notable exceptions. For example, Ramirez-Marquez and Sauser [31] developed a Mixed-Integer Non-Linear Programming (MINLP) model to optimize the SRL of systems through the allocation of limited human and financial resources for projects; a customized metaheuristic algorithm was also developed to solve the resulting model. A multi-objective extension of this model was later proposed [32]. A Petri net-based approach for optimizing SRL has also recently been reported [33].

Table 2. SRL level definitions (Sauser et al., 2008).

Level	SRL Definition
0.10–0.39	Concept refinement.
0.40–0.59	Technology development.
0.60–0.79	System development and demonstration.
0.80–0.89	Production and deployment.
0.90–1.00	Operations and support.

There remains a significant research gap in the development of models for optimal allocation of limited financial resources for innovation projects. The green technologies in such projects can either be independent of each other, or mutually interdependent. In the latter case, they act as components that are linked together in a system-level network. Process Integration (PI) strategies based on Pinch Analysis (PA) and Mathematical Programming (MP) can be used to optimize the use of financial resources in such problems. El-Halwagi [34] defined PI as a "*holistic approach which emphasizes the unity of the process*." PI methodology seeks to economize the use of a valuable resource (e.g., energy, water, etc.) through optimal allocation; it also emphasizes the value of providing insights for engineers and managers as an aid to decision-making [35]. Developments in PI methodology and applications are reported in conferences dedicated to the topic [36]. The most significant advances can be found in a handbook [37] and a recently published comprehensive review paper [38]. Recent non-conventional extensions as well as new prospective applications of PI were discussed by Tan et al. [39]. Clearly, the general PI approach of optimizing the use of a valuable resource can apply to financial resources as well. Zhelev [40] first proposed the use of PI methodology to financial aspects of engineering problems. Then, Bandyopadhyay et al. [41] developed a graphical approach for allocating funds to different projects based on expected return on investment (ROI). This procedure used the source-sink concept used for a broad range of PI problems [42]. A subsequent paper by Roychaudhuri et al. [43] modified this method and applied it to the problem of funding multiple energy conservation projects. Roychaudhuri and Bandyopadhyay [44] then developed a Mixed Integer Linear Programming (MILP) model based on the source-sink concept.

Viewing the research gap in the literature, there is a need to develop systematic decision support tools for evaluating how financial resources can be allocated for the development of emerging technologies with the objective of maximizing their success. In this paper, two MILP models are developed for specific problems pertaining to fund innovation in green technologies, which includes the development and deployment of renewable energy sources and negative emission technologies (NETs). The first model, which is a bi-objective MILP, is developed for allocating financial resources from multiple funds (sources) to multiple independent innovation projects (sinks). For both sources and sinks, quality restrictions are defined by ROI and TRL. The second model is a robust MILP to maximize the SRL of a network of interdependent component technologies. The model is also formulated to account for inherent uncertainties in project costs, which in practice usually leads to cost overruns [31]. For each model, a formal problem statement is first given, followed by the mathematical formulation and an illustrative case study on biorefinery technologies, which present significant potential to improve the sustainability of industrial supply chains [45]. Nevertheless, the main contribution of this paper is the modelling framework for optimizing financing decisions in green technology innovation. The methodology developed here is generic in nature, and can be extended to applications in other sectors. Practical implications for general engineering project management are then discussed. Finally, conclusions and prospects for future work are discussed.

2. Model 1

The first model is intended for optimal matching of funding sources and innovation projects based on ROI and TRL considerations. It is formulated as a bi-objective MILP model based on source-sink allocation. The two objectives represent aggressive and conservative ROI estimates that represent preferences of optimistic and pessimistic decision-makers, respectively.

2.1 Model 1: Formal Problem Statement

The source-sink superstructure for this problem is shown in Figure 1.

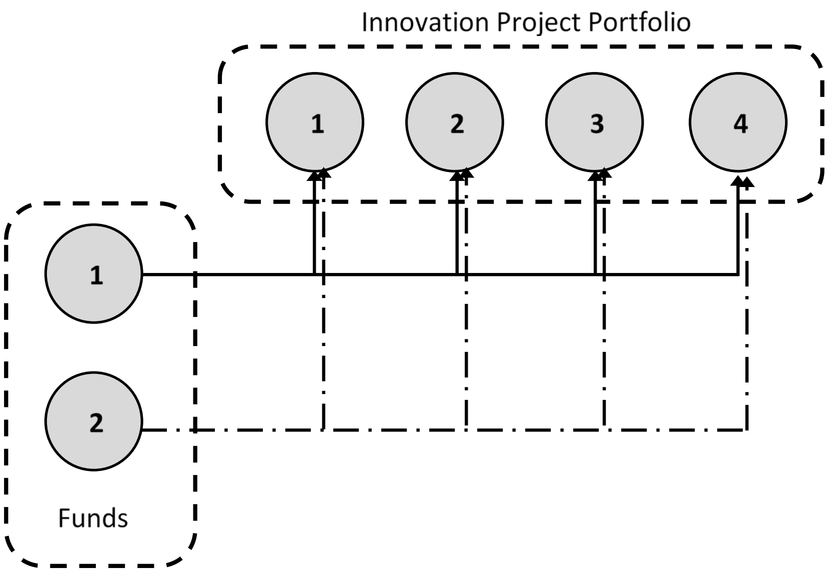

Figure 1. Superstructure for Model 1 fund allocation problem.

The formal problem may be stated 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.

2.2 Model 1: Development and Formulation

The bi-objective MILP model is formulated as follows:

$$\max \Sigma_j \mathrm{ROI}_j^{U} \mathrm{P}_j b_j \quad \text{(Eq.1.1)}$$

$$\max \Sigma_j \mathrm{ROI}_j^{L} \mathrm{P}_j b_j \quad \text{(Eq.1.2)}$$

subject to:

$$\Sigma_j\ r_{ij} \leq F_i \qquad \forall I \qquad \text{(Eq.1.3)}$$

$$\Sigma_i\ r_{ij} = P_j\ b_j \qquad \forall j \qquad \text{(Eq.1.4)}$$

$$\Sigma_j\ ROI_j^L\ r_{ij} \geq FROI_i\ \Sigma_j\ r_{ij} \qquad \forall i \qquad \text{(Eq.1.5)}$$

$$r_{ij} \leq M\ b_{ij} \qquad \forall i, j \qquad \text{(Eq.1.6)}$$

$$b_{ij} \in \{0, 1\} \qquad \forall i, j \qquad \text{(Eq.1.7)}$$

$$b_{ij} \leq (TRL_j / FTRL_i) \qquad \forall i, j \qquad \text{(Eq.1.8)}$$

$$b_j \in \{0, 1\} \qquad \forall j \qquad \text{(Eq.1.9)}$$

where ROI_j^U is the optimistic estimate of ROI of project *j*; ROI_j^L is the pessimistic estimate of ROI of project *j*; 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 (Eqs. 1.1 and 1.2). To ensure that information on probability extremes are not lost, the objectives that represent attitudes of risk-tolerant and risk-averse decision makers are kept separate, as in the Partitioned Multi-objective Risk Method (PMRM) [46]. Eq. 1.3 ensures that any given fund is not over-utilized, while Eq. 1.4 ensures that any selected project is fully funded. In this work, it is assumed that each project can be funded with multiple funding sources. The average conservative ROI for all projects supported by any given fund should be at least equal to its specified minimum ROI threshold, $FROI_i$ (Eq. 1.5). Eqs. 1.6 and 1.7 relate each flow of financial resource to a corresponding binary variable. A fund will only be used to support projects that meet its TRL threshold (Eq. 1.8). This constraint is conceptually similar to "staircase" composite curves in some PI applications [47]. Eq. 1.9 defines the binary variable for project selection. The Pareto frontier of this bi-objective MILP can be determined using the ε-constraint method, which entails converting it into a single-objective MILP with the second objective being converted into a parametric constraint. The global optimum of this MILP model can be determined using the branch-and-bound algorithm commonly found in commercial optimization software.

2.3 Case Study 1

In this case study, different emerging technologies for oil palm biomass processing are considered. It is implemented using the commercial software LINGO 17.0 using an i7-6500U CPU at 2.50 GHz with 8.00 GB RAM. The oil palm industry is an important agro-industrial sector in developing countries such as Malaysia and Indonesia in Southeast Asia, and Nigeria in Africa. This sector generates large quantities of residual biomass such as oil palm fronds (OPF), empty fruit bunches (EFB), palm kernel shell (PKS) and mesocarp fibre. These by-products/wastes are a potentially abundant resource which can be utilized to generate renewable energy and value-added products, while also improving the sustainability of the entire industry [48]. Such gains can be made possible if new technologies for biomass processing and utilization are commercialized. In this case study, the funding sources and the projects to be funded are shown in Tables 3 and 4, respectively.

Table 3. Fund data for Case Study 1.

Fund type	Available amount (US$)	Minimum TRL threshold	Minimum ROI threshold, $FROI_i$ (%)
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 4. Project data for Case Study 1.

Project	Cost (US$)	TRL	Optimistic ROI (%) ROI_j^U	Pessimistic ROI (%) ROI_j^L
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

The ROI values give the cumulative returns over an assumed 20-year economic life. Upper and lower bounds are given to reflect uncertainties in the profitability projections. It can be seen that the margins of uncertainty are larger for lower TRL projects. On the other hand, at higher TRL, the ROI can be predicted more precisely. In general, this means that risk-averse managers of the different funds will be less inclined to support immature technologies due to higher techno-economic risk.

The bi-objective MILP model can be solved using the ε-constraint method to yield a Pareto frontier with just two points. Solving the model using Eq. 1.1 as the objective function gives an optimal optimistic or aggressive ROI of US$42.925 million. For this solution, funds must be allocated as shown in Table 5; the worst-case ROI that results from this solution can be found using Eq. 1.2 to be US$33.388 million. For this solution, funds must be allocated as shown in Table 6. These solutions clearly illustrate the options available depending on the attitude to risk. The decision-maker can either be aggressive by optimizing the optimistic ROI, while running the risk of realizing an inferior worst-case ROI. Alternatively, he can be conservative by optimizing the pessimistic ROI, and forego the potential to achieve a higher best case ROI for the portfolio. In both solutions, four of the projects (i.e., the biomass-fired power plant, dried long fibre plant, biofertilizer plant, and palm pellet plant) are all funded through the combination of industry funding, crowd funding and angel investor funding.

Table 5. Funding allocation based on optimistic ROI in Case Study 1.

Project	Government grant	Industry funding	Crowd funding	Angel investor funding
Integrated biogas and wastewater treatment system				
Biomass-fired power plant		1,000,000	4,500,000	

Dried long fiber plant			1,500,000	
Biofertilizer plant		3,750,000		
Palm pellet plant				2,000,000
Biochemical process plant	7,500,000			

Table 6. Funding allocation based on pessimistic ROI in Case Study 1.

Project	Government grant	Industry funding	Crowd funding	Angel investor funding
Integrated biogas and wastewater treatment system	6,250,000			
Biomass-fired power plant		1,000,000	4,500,000	
Dried long fiber plant			1,500,000	
Biofertilizer plant		3,750,000		
Palm pellet plant				2,000,000
Biochemical process plant				

They differ only in how the government grant is allocated. Both Projects 1 and 6 are ineligible to be supported by other funding schemes due to their low TRL. At the same time, their combined cost makes it impossible for both to be supported simultaneously by the government grant. In the pessimistic solution, Project 1 (the integrated biogas and wastewater treatment system) is funded, while in the optimistic solution, Project 6 (the biochemical process plant) is chosen instead. This case study illustrates how funds can be allocated based on either an optimistic or pessimistic outlook, depending on the risk aversion level of the TBI manager.

3. Model 2

The second model is intended for optimal allocation of funds to optimize the SRL of a network of interdependent technologies. It is formulated as a robust MILP model that seeks to maximize SRL by allocating funds to improve pairwise IRL of components. This approach is used because both IRL and SRL tend to lag behind TRL in maturity level [31]. For example, in the case of CCS, many of the component technologies for capturing, transporting and sequestering CO_2 are relatively mature, while the full-scale application of an integrated CCS system remains less established.

3.1 Model 2: Formal Problem Statement

The problem addressed by the MILP model may be stated formally as follows:

- Given *N* number of interdependent emerging green technologies;
- Given a constant TRL vector describing the current maturity level of each emerging green technology *j*, TRL_j;
- Given a variable IRL matrix describing the current maturity level of pairwise coupling among the interdependent emerging green technologies;
- Given that, for each pair of emerging green technologies, there is an incremental cost estimate in order to reach higher IRL levels;
- Given a total budget constraint for system development, R;
- The problem is to determine the allocation of limited funds to maximize SRL without exceeding the total budget.

Note that the problem can also be framed in an alternative manner, so as to minimize total project cost needed to achieve a predefined SRL target. The basic deterministic form of the model may also be easily extended into a robust formulation to account for cost uncertainties inherent in innovation projects.

3.2 Model 2: Development and Formulation

For a system with *N* component technologies, Sauser et al. [30] defines the calculation of *SRL* from component TRL values and IRL as follows:

$$SRL_j = (1/n_j)\ \Sigma_k\, (IRL_{jk}/9)(\mathrm{TRL}_k/9) \qquad \forall\, j \qquad \text{(Eq.2.1)}$$

where SRL_j is the System Readiness Level of technology j, IRL_{jk} is the Integration Readiness Level of technology j with technology k, TRL_k is the Technology Readiness Level of technology k, and n_j is the number of non-zero interdependencies of technology j as signified by IRL_{jk}. Note that $IRL_{jk} = 0$ if technologies j and k have no functional interface based on system topology, and that $IRL_{jk} = 9$ for $j = k$ (i.e., self-interaction of any given technology is assumed to be at the highest possible level). The overall SRL can then be computed as the average of the component SRL_j values:

$$SRL = (1/n)\ \Sigma_j\ SRL_j \qquad \text{(Eq.2.2)}$$

where n is the number of component technologies in the system. This basic model gives SRL as a function of given TRL and IRL values.

The proposed MILP model may then be developed from these basic calculations as:

$$\max SRL \qquad \text{(Eq.2.3)}$$

subject to:

$$SRL = (1/n)\ \Sigma_j\ SRL_j \qquad \text{(Eq.2.4)}$$

$$SRL_j = (1/n_j)\ \Sigma_k\ (\mathrm{IRL}_{jk}/9)\ (\mathrm{TRL}_k/9) \qquad \forall\ j \qquad \text{(Eq.2.5)}$$

$$IRL_{jk} = \mathrm{IRL}_{jk}^* + \Sigma_p\ b_{jkp} \qquad \forall\ j, k \qquad \text{(Eq.2.6)}$$

$$\Sigma_j\ \Sigma_k\ \Sigma_p\ C_{jkp}\ b_{jkp} \leq R \qquad \text{(Eq.2.7)}$$

$$b_{jkp+1} \leq b_{jkp} \qquad \forall\ j, k, p \qquad \text{(Eq.2.8)}$$

$$b_{jkp} \in \{0, 1\} \qquad \forall\ j, k, p \qquad \text{(Eq.2.9)}$$

where parameter TRL_k is the TRL of technology k, parameter IRL_{jk}^* is the initial IRL of the coupling between technologies j and k, and b_{jkp} is a binary variable signifying the increment of IRL_{jk} by one step, C_{jkp} is the corresponding estimated cost to achieve a one point increase of IRL_{jk}, and R is the total project budget. The objective function is to maximize SRL (Eq.2.3), which is computed as originally defined (Eq.2.4 to 2.5). The final selected IRL_{jk} of any pair of component technologies is given by the initial value

IRL_{jk}* plus the cumulative number of incremental steps (Eq. 2.6). Incremental gains in IRL_{jk} throughout the system are constrained by the total cost of achieving these gains, which must not exceed the available financial resources (Eq.2.7). Incremental steps in IRL_{jk} can only be activated if previous increments have already been selected (Eq.2.8). Finally, the variables b_{jkp} are restricted to binary values (Eq.2.9). Like the previous model, this MILP formulation can be readily solved to global optimality, without significant computational issues, by branch-and-bound solvers found in typical commercial optimization software.

The budget constraint can be readily modified to account for inherent cost estimate uncertainties which often result in cost overruns in innovation projects [31]. In this case, the parametric approach proposed by Carlsson and Korhonen [49] can be applied to yield a robust generalization of (Eq. 2.7):

$$\Sigma_j \Sigma_k \Sigma_p \ (C_{jkp} + \alpha\Delta C_{jkp})\ b_{jkp} \leq (R - \alpha\Delta R) \qquad \text{(Eq.2.10)}$$

where parameter α indicates the risk aversion level of the decision-maker, parameter ΔC_{jkp} is the potential deviation from the nominal cost C_{jkp} , and parameter ΔR is the potential deviation from nominal budget R. Note that $\alpha \in [0, 1]$, where 0 indicates an optimistic (risk-tolerant) decision-maker, and 1 indicates a conservative (risk-averse) decision-maker. The original deterministic MILP can be taken as a special case of this more general formulation, with $\Delta C_{jkp} = \Delta R = 0$.

3.3 Case Study 2

This biorefinery case study is presented to illustrate the model capabilities. The numerical example is implemented using the commercial software LINGO 17.0, using an i7-6500U CPU at 2.50 GHz with 8.00 GB RAM. This case again deals with the common problem of using abundant, underutilized biomass resources in countries with well-developed agro-industrial sectors [48]. Thus, a biorefinery is to be built to demonstrate the scalable utilization of such biomass for producing biocrude with very low net carbon emissions. The biorefinery system consists of six component green technologies, which are listed along with their respective TRLs in Table 7. The simplified process flow diagram is shown in Figure 2. Raw biomass is first pre-treated to ensure uniform physical quality to enhance the performance of biomass conversion into products. In addition, the moisture content of the biomass is also reduced to suit the requirement of the downstream process. A gasifier then converts the pre-processed biomass into syngas and biochar, as well as minor quantities of bio-oil and ash (the latter streams are not considered further in this example). The syngas goes to a gas cleaning unit, and is then either be used as sources in combined heat and power (CHP) unit (which provides the energy requirements of the complex), and gas-to-liquid (GTL) processing unit which generates liquid biocrude as the main product of the plant. On the other hand, the biochar is exported from the site for application to soil, which results in partial carbon sequestration [50].

Table 7. TRLs of component technologies in biorefinery Case Study 2.

Component	Process Description	TRL
Technology 1	Biomass pre-processing	9
Technology 2	Biomass gasification	8
Technology 3	Syngas cleaning unit	8
Technology 4	GTL process	8
Technology 5	CHP system	9
Technology 6	Biochar application	9

Interactions among component technologies can be summarized as shown in Figure 3, whose links signify non-zero elements in the IRL matrix. The corresponding initial numerical values of the IRLs are given in Table 8, while the ranges of incremental cost estimates to improve the IRLs are given in Table 9.

The MILP model is then solved to determine the optimal SRL assuming a total available budget of €1.4–1.6 million. The risk aversion parameter α can also be varied parametrically between extreme values of 0 and 1 to give a locus of solutions for different risk tolerance levels. These solutions are shown in Table 10. Note that, for a risk-tolerant decision-maker (α = 0, 0.2), the optimal solution reaches the highest SRL band of at least 0.9, which indicates nearly full maturity (see Table 2). More conservative solutions fall just short of the threshold SRL value of 0.9, as a result of hedging for cost overruns in the innovation process. In all cases, it is also noted that the model selectively allocates funds to technology couplings for which gains are relatively inexpensive, which in this case refers to coupling of the CHP unit with other major processes in the plant. The low cost can be attributed to the relative technological simplicity of provision of electricity and steam as a form of technology coupling. More complex couplings, on the other hand, are selected relatively infrequently due to higher costs and higher uncertainty, which is indicative of technological investment risk.

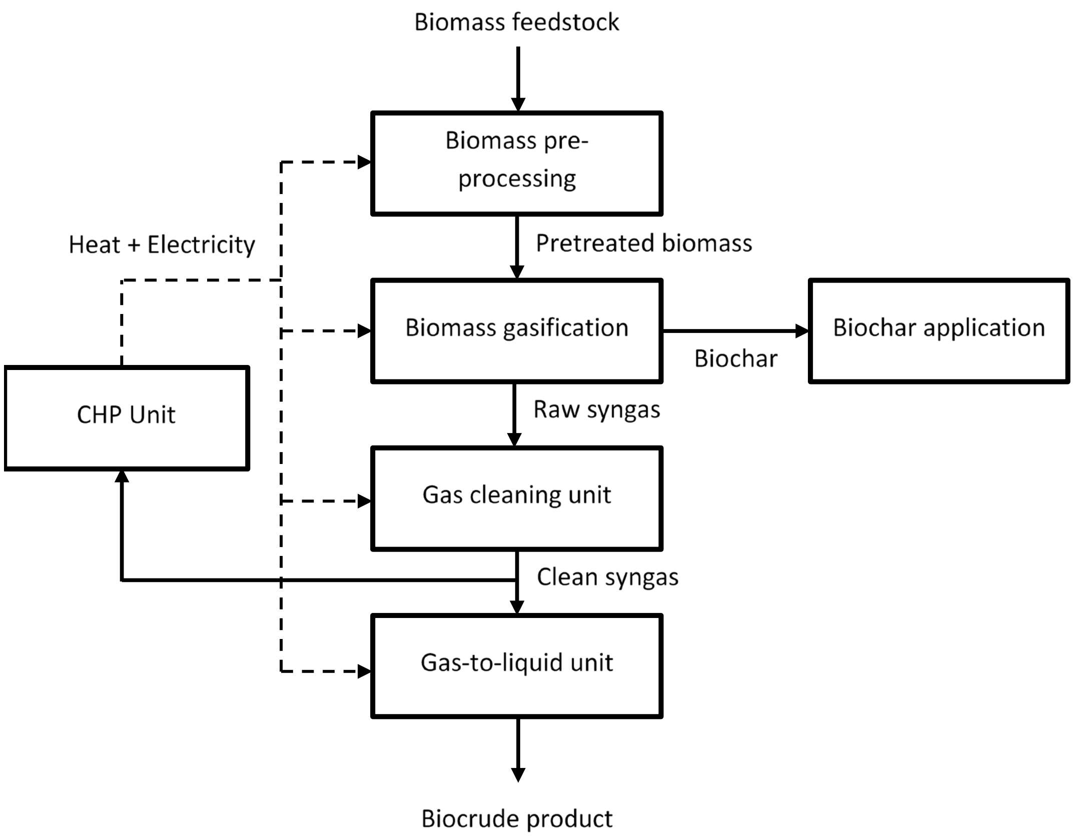

Figure 2. Biorefinery process flow diagram in Case Study 2.

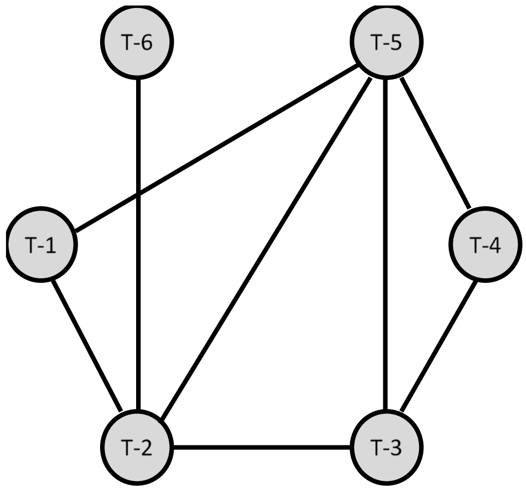

Figure 3. Biorefinery system concept diagram showing technology coupling in Case Study 2.

Table 8. Initial IRLs of component technologies in biorefinery Case Study 2.

	Technology 1	Technology 2	Technology 3	Technology 4	Technology 5	Technology 6
Technology 1	9	7	0	0	8	0
Technology 2	7	9	7	0	8	6
Technology 3	0	7	9	7	6	0
Technology 4	0	0	7	9	8	0
Technology 5	8	8	6	8	9	0
Technology 6	0	6	0	0	0	9

Table 9. Estimated cost in €1000 to achieve incremental increase in IRLs in biorefinery Case Study 2.

	IRL = 7	IRL = 8	IRL = 9
Technologies 1, 2	0	80–100	50–60
Technologies 1, 5	0	0	60–80
Technologies 2, 3	0	180–260	160–260
Technologies 2, 5	0	0	60–85
Technologies 2, 6	250–300	300–400	220–280
Technologies 3, 4	0	220–300	240–330
Technologies 3, 5	120–180	160–250	200–280
Technologies 4, 5	0	0	80–100

Table 10. Locus of optimal solutions for biorefinery Case Study 2.

	Initial	Degree of conservatism (α)					
		1	0.8	0.6	0.4	0.2	0.1
SRL	0.860	0.878	0.884	0.890	0.893	0.900	0.901
SRL_1	0.860	0.963	0.963	0.963	0.963	0.963	0.963
SRL_2	0.783	0.894	0.872	0.916	0.872	0.916	0.872
SRL_3	0.735	0.762	0.815	0.762	0.840	0.787	0.867
SRL_4	0.823	0.860	0.893	0.860	0.926	0.893	0.926
SRL_5	0.812	0.894	0.914	0.894	0.914	0.894	0.933
SRL_6	0.796	0.895	0.846	0.944	0.846	0.944	0.846
$IRL_{1,2}$	7	9	9	9	9	9	9
$IRL_{1,5}$	8	9	9	9	9	9	9
$IRL_{2,3}$	7	7	7	7	7	7	7
$IRL_{2,5}$	8	9	9	9	9	9	9
$IRL_{2,6}$	6	8	7	9	7	9	7
$IRL_{3,4}$	7	7	8	7	9	8	9
$IRL_{3,5}$	6	7	8	7	8	7	9
$IRL_{4,5}$	8	9	9	9	9	9	9
Project Cost (€1000)	0	1,305	1,380	1,439	1,506	1,529	1,575

4. Practical Implications for Project Management

Technological innovation resulting from research and development will be essential to address environmental issues that are associated with energy systems. Decision-makers in industry and government invariably face the challenge of allocating limited financial resources to support competing (or complementary) projects intended to develop new innovations in green energy technologies. Decision support tools such as MP models can facilitate efficient allocation of such resources based on the best information at hand with various consideration. The two case studies provide key insights for generic project management problems in the commercialization of green technologies. The two models developed here apply to problems involving multiple independent and interdependent innovations projects, respectively. In general, PI is intended to provide insights for decision support; thus, effective models should give both optimal solutions, and further information on the characteristics of the solutions [35]. In other words, the practitioner also needs information on how the solution may change with respect to assumptions, and if other alternative solutions exist. Such issues are addressed by the models developed in this work. Model 1 addresses the problem of allocating funds to multiple competing projects. In such cases, ROI and TRL provide information of how the matches can be made depending on the characteristics of the sources and sinks. Uncertainties in ROI projections are treated as separate objective functions, which account for the extremes of risk-tolerant (optimistic) and risk-averse (pessimistic) attitudes that a decision-maker may take. In contrast, merely taking an average ROI will result in failure to account for information about extreme scenarios that may occur in the development of green technologies.

On the other hand, Model 2 addresses the relatively low maturity of the coupling or interface between green technologies in a complex system, and the cost uncertainties that are often encountered in planning efforts to increase maturity levels. The first issue is clearly illustrated in the example by the use of biochar application to soil as a form of carbon sequestration. Taken individually, the thermochemical production of biochar and its application to soil via mechanical tillage are relatively mature technologies; however, their integration into a full-scale system for commercial carbon sequestration is still unproven. This case thus gives a clear example of IRL lagging behind component TRLs in green technology systems. Meanwhile, in practice, innovation and commercialization projects are often characterized by cost overruns due to failure to accurately predict maturity gains from development efforts [31].

These MILP models can thus be very useful for practical decision-making in projects involving the commercialization of green technology systems, as it can provide clear insights on the impacts of technology couplings that act as bottlenecks at the system level. Just as PA determines how resources should be allocated in conventional PI problems, the bottlenecks identify where financial resources can be best allocated for maximum benefit. The provision to handle investment risk is also an important aspect that can allow different solutions to be compared by decision-makers (e.g., project managers and engineers) before a final selection is made. In addition, the capability of the MILP models to be implemented using commercial spreadsheets or dedicated optimization software increases the potential for practical use for real problem-solving. Such practical decision support capability is essential for greater commercial success of green technologies in the future.

5. Conclusion

In this work, two MILP models have been developed to optimize the funding of innovative green technologies. The first model is a bi-objective MILP to match and allocate funds to different innovation projects based on ROI and TRL considerations, using an extension of the source-sink formulation used in many PI problems. The second model is a robust MILP model to optimize the allocation of limited innovation funds towards the development of a process network of interdependent emerging green technologies, so as to maximize SRL. The integration of TRL, IRL and SRL in the evaluation of innovations in green energy technologies reveal where bottlenecks for eventual deployment lie. The parametric robust formulation allows a range of solutions to be generated to properly account for the risk tolerance of the decision-maker. Policies for the selection of which green technology innovations to be funded should take into consideration not just individual technology maturity, but also technology interdependencies which determine over-all system readiness in value chains. Case studies on biorefinery technologies have been solved to illustrate the usefulness of these models.

Future work can extend these models by relaxing the simplifying assumptions used in the current formulations. For example, refinement of the SRL concept itself may improve its usefulness. Dynamic or multi-period variants of both models can be developed to take temporal effects into account. Alternative approaches based on graphical PA or P-graph approaches can also be developed. Another potential future extension of the second model in this work is to relax the assumption of a fixed system TRL matrix, followed by linearization of the resulting MINLP; such a linearization will allow the rigorous determination of the global optimum.

Conflict of Interest

The authors declare that they have no conflict of interest.

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Nomenclature

Sets

S Set of fund sources; $S = \{1, 2, \cdots, M\}$

D Set of innovation projects, emerging technologies or sinks; $D = \{1, 2, \cdots, N\}$

Indices

i Index for fund sources, $i \in S$

j, *k* Index for innovation projects, technologies or sinks; $j \in D$

p Index for one-step incremental improvement in IRL

Parameters

α Risk aversion level

C_{jkp} Cost to achieve *p*-th one step increment in IRL of technology *j* with technology *k*

ΔC_{jkp} Cost tolerance to achieve *p*-th one step increment in IRL of technology *j* with technology *k*

F_i Size of fund *i*

$FROI_i$ Minimum return on investment threshold for fund source i

$FTRL_i$ Minimum TRL threshold for fund source i

$IRL_{ij}*$ Initial IRL of technology *j* with technology

M Arbitrary large number

n Number of component technologies in system

n_j Number of non-zero interactions of technology *j* within the system

P_j Cost of project *j*

R Budget limit/contraint

ROI_j^L pessimistic estimate of return on investment for project j

ROI_j^U optimistic estimate of return on investment for project j

ΔR Budget limit tolerance

TRL_j TRL of project or technology *j*

Variables

b_j	Binary variable on the decision whether project j is funded or not
b_{ij}	Binary variable on the decision on whether to allocate resources from fund i to project j
b_{jkp}	Decision to achieve pth one step increment in IRL of technology j with technology k
IRL_{jk}	Final IRL of technology j with technology k
r_{ij}	Allocation of financial resource fund i to project j
SRL	Overall SRL
SRL_j	SRL of technology j

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