INVESTEMENT DECISION STRATEGY FOR SUSTAINABLE BIOREFINERIES

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ABSTRACT

Biorefineries need to maximize their profit potential and scope for multiple products; however, technological options for integration include biochemical and thermo-chemical routes. Process systems engineering is employed to deal with the complex problem of process synthesis in multiproduct biorefineries. Nevertheless, existing approaches do not consider the possibility of independent investment projects. Current work presents a new methodology for the synthesis of processes and investment decisions in general. The investor can propose the maximum number of processes that can potentially be integrated with the original investment. Modularity levels treat processes independently or as an integrated group (module). The method can automatically create all the candidate integrated modules and screen the possible integration options based on the potential profit or any other desired objective function. First results show that even processes with negative potential profit turn into profitable investments if combined with beneficial integration. This approach is still in its infancy and in future work is intended to be expanded with more modeling layers and a wider range of applications.

Keywords: Process Synthesis, Biorefinery, Modular, Optimization, MILP

INTRODUCTION

Almost twenty years after the Kyoto protocol, the United Nations Climate Change Conference, COP 21, agreed, once again, on the need to reduce the carbon output.[1] Even though many studies support that bioprocesses can mitigate the greenhouse gas emissions (GHG) [2-4], policy makers still have their doubts [5]. As a result, each biorefinery technology needs to ensure its profitability in order to reach the industrialization stage. Entrepreneurs foresee the potential in bioprocesses but hesitate to invest in other technologies than biofuels (bioethanol, biomethane, and biodiesel) [6], mainly due to the existence of numerous alternatives and the high investment risk in pioneer technologies. Systems engineering methods have been recruited to address the complex task of process synthesis in bioprocesses.

Yuan et al. (2013), studied the opportunities and potential challenges for the process synthesis posed by the biorefinery process, setting the synthesis of conventional processes as a starting point. They identified three kinds of process synthesis approaches scoping to be cost effective: hierarchical decomposition, mathematical programming, and hybrid [7]. Applications on synthesis and process integration applications also exist in the literature [8]. Floudas and Grossman (1994) pointed out that algorithmic methods in process synthesis involve four major components: (a) Representation of space of alternatives; (b) General solution strategy; (c) Formulation of optimization model; (d) Application of solution method [9]. Many applications use superstructures as their representation of space alternatives, applying MILP or MINLP optimization strategies [10-12] and/or decomposition methods [13, 14]. Recent applications combine heat, water, and process integration with cost and environmental objectives by decomposing the problem into process synthesis, process integration, and flowsheeting levels [15, 16].

The representation of space of alternatives can range from conceptual to detailed flowsheet descriptions. Nevertheless, this stage is still user-dependent with the risk to omit useful alternatives or to include unnecessary complexity. Methodologies based on semantic web, ontologies, have been introduced for the automatization of the alternative space search [17, 18]. However, technological options include biochemical and thermo-chemical routes, which, at some point, would need to integrate with each other. The integration becomes more complicated when trying to exploit possible trade-offs, following paradigms of Industrial Symbiosis [19, 20]. Moreover, the revelation of one optimal solution rarely can convince the potential investors. This might be the reason for the systematic search of alternatives in bioprocesses using the method of integer cuts[21]. Yet, existing methodologies consider the total investment and they do not treat each candidate process as an independent investment project.

Current work proposes a mixed integer linear programming (MILP) model to screen among different investment options, which are created automatically. The approach presumes that a process at the stage of industrialization (main investor) wants to examine the option to collaborate (associate) or to adopt (integrated investment) a process which valorizes its main product and/ or by-products. The main investor can choose the maximum number of processes to be adopted, set a budget limitation, and express a preference over the type of the products. Depending on the margin of profit willing to sacrifice, the main investor can request a favor on specialties over commodities or a certain consideration of chemicals over energy products.

METHODOLOGY

As a first stage, current approach builds automatically the space of alternatives in the form of modules. Then follows the search for the module combination with the maximum potential profit in the form of a mixed integer linear programming (MILP). Parameter α is employed to list alternative solutions in relation to potential profit diminution. The estimation of the cost and income of each module is beyond the scope of this paper.

- Space of alternatives

Given a set of known processes (I) and the maximum desired number of processes to be combined together (m), we can find all the possible investment configurations. We assume that there are different investment levels: level 1 invests in one process, level 2 invests in two processes etc. Each process can be combined with all the other processes but can exist only once per level. Since each level denotes a group of processes in a different structure, we decide to call each group "module" and all the modules in each level j "level of modularity" (L_j). It is obvious that for j=1, L_1=I $\left(I \subset L_j\right)$.

The problem can be mathematically expressed as:

$$\left\{I_1,..,I_j\right\} \in L_j \quad IF \quad \left\{I_1,..,I_{j-1}\right\} \in L_{j-1} \quad AND \quad ord\ of\ element\left(I_j\right) > ord\ of\ element\ \left(I_{j-1}\right) \quad (1)$$

$\{I_1,\ldots, I_j, \ldots, I_m\}$ are alias namespaces of set I.

When the user wants to create modules where the product of one process feeds the other, an additional constraint is necessary. In that case, based on the known yield of product p from a process i with feed f (Yield (i,f,p)), we can define an additional constraint for the existence or not of the link between process i and k:

For each component c

$$\sum_f Yield(i,c,f) \neq 0 \quad AND \quad \sum_p Yield(k,p,c) \neq 0 \quad , \quad where \quad f,p \subset c \qquad (2)$$

Expression (2) allows the link only if the product of process i exists as feed in process k. The combination of (1) and (2) will create all the possible combinations based on a value chain tree.

- Module Synthesis

Given the cost (Cost(L_j)) and the income (Income(L_j)) of each module in all modularity levels, we can find which module has the minimum cost or the maximum profit potential. We also define that each module has reason to exist only if its cost is less than all the modules, which contain the same processes in lower modularity levels. This definition is expressed as

$$\sum_{l=1}^{j-1} Cost(L_l) > Cost(L_j) \quad ,(I \cup L_l) \cap (I \cup L_j) \tag{3}$$

We employ a binary variable Y(L) for the existence or not of each module, while U is a very big number. Since the investor might be willing to pay a little bit more, we also introduce parameter α, which denotes the deviation from the strict inequality.

$$\sum_{l=1}^{j-1} Cost(L_l) - Y(L_j) \cdot Cost(L_j) \cdot \alpha^{-1} \geq (Y(L_j) - 1) \cdot U \quad ,(I \cup L_l) \cap (I \cup L_j) \tag{4}$$

The constraint that each process exists only once per module is expressed as

$$\sum_{l=1}^{j-1} Y(L_l) + Y(L_j) \leq 1 \quad ,(i \epsilon L_l) \cap (i \epsilon L_j) \tag{3}$$

The objective function is the maximization of the potential profit.

$$maxPProfit = \sum_{i} Y(L_j) \cdot \left(Income(L_j) - Cost(L_j)\right) \tag{4}$$

ILLUSTRATIVE EXAMPLE

The scope of this paper is to display the potential of the modular approach and not to demonstrate the cost estimation method. For this reason, current work presents a theoretical example using six hypothetical processes: I= {A, B, C, D, E, F} with known yields (Table 1). The maximum possible modularity level is m=6, which means that the modularity set will have six subsets: L={L_1,L_2,L_3,L_4,L_5,L_6}.

Table 1. Yield data

i	p	F	Yield
A	C2	C1	0.80
A	C3	C1	0.20
B	C4	C2	0.70
C	C5	C2	0.60
D	C6	C3	0.85
E	C7	C5	0.95
F	C8	C7	0.95
F	C9	C7	0.03

- Space of alternatives

When creating modules by applying the unconstrained method (Eq.1), the resulted modules are all the possible combinations per modularity level.
L_1= {A, B, C, D, E, F}
L_2= {AB, AC, AD, AE, AF, BC, BD, BE, BF, CD, CE, CF, DE, DF, EF}
L_3= {ABC, ABD, ABE, ABF, ACD, ACE, ACF, ADE, ADF, AEF, BCD, BCE, BCF, BDE, BDF, CDE, CDF, CEF,DEF}
L_4= {ABCD, ABCE, ABCF, ABDE, ABDF, ABEF, ACDE, ACDF, ACEF, ADEF, BCDE, BCDF, BCEF, BDEF, CDEF}
L_5= {ABCDE, ABCDF, ABCEF, ABDEF, ACDEF, BCDEF}
L_6= {ABCDEF}

Based on the yield per process data (Table 1), it is easy to find out how does the value chain tree look like (Figure 1). Nevertheless, it is not that obvious to find all the possible combinations among value chain processes. When creating modules by applying the constrained method (Eq.1 & 2), the resulted modules are
L_1= {A, B, C, D, E, F}
L_2= {AB, AC, AD, CE, EF}
L_3= {ABC, ABD, ACD, ACE, CEF}
L_4= {ABCD, ABCE, ACDE, ACEF}
L_5= {ABCDE, ABCEF, ACDEF}
L_6= {ABCDEF}

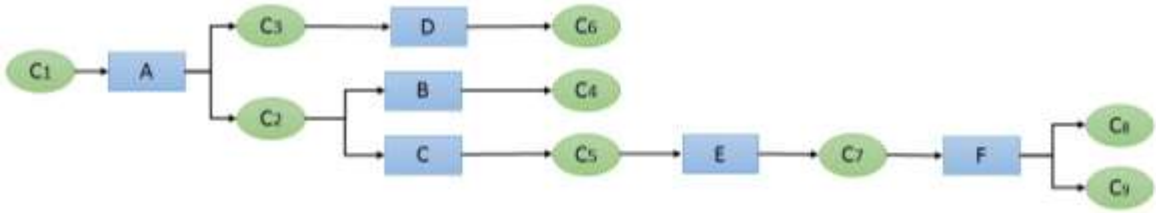

Figure 1. *Resulted Value Chain Tree.*

- Module Synthesis

For the screening among the modules we need cost and income data. We postulate that the availability of C_1 is 100kg/hr, the operation year has 8600 h/yr, and that the depreciation time is 10yr. Furthermore, if two processes share the same feed component (in our case C_2), then the feed stream is split in half (sf=0.5). This is not an optimized split fraction, but it is used for demonstration purposes. In that case the capital cost estimation follows the six-tenths-factor method for scaling equipment cost [22]. It is also assumed that components have different buy and sell price (Table 2) and that in the case of a module existence we need to buy the feed only for the first process. For example, in the case of ACD module we only need to buy C_1, and in the case of CEF we only need to buy C_2.

Table 2. *Component buy - sell price.*

[$/tn]	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Buy	90	180	300	390	380	600	590	750	900
Sell	180	250	410	490	480	750	710	890	1200

The cost of the modules includes the annualized equipment cost (CCost) and the feedstock cost (FCost), while the income comes only from selling the final product. The results for level 1 (independent processes) are presented on Table 3.

Table 3. *Individual processes.*

[M$/yr]	A	B	C	D	E	F
CCost	120.00	88.00	78.00	29.00	52.00	61.00
FCost	77.40	123.84	123.84	51.60	156.86	231.37
Income	242.52	235.98	198.14	109.65	278.43	345.69
PProfit	45.12	24.14	-3.70	29.05	69.57	53.31

Two cases are examined: one where the benefit of integration is homogenous per level (L2: -10%, L3: -15%, L4:-22%, L5:-32%, L6:-42%) and one where is random per module (from -51% to -1%). The random benefit is a more realistic assumption, but the homogeneous assumption serves for demonstration purposes. Apart from only presenting the optimum solution, Figure 2 shows how the optimal solution is affected by the parameter α, introduced in Eq. 4. This parameter α actually searches for a solution where the investor is willing to sacrifice a part of the profit in order to favor the modular integration with another process. Each solution proposes whether some processes should be integrated as a module or operate independently (Table 4).

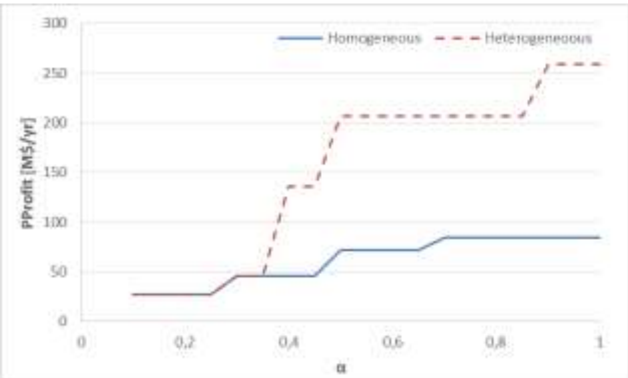

Figure 2. *Potential profit vs. α.*

Table 4. Modules vs. α.

α	[1.0 - 0.9]	(0.9 - 0.7]	(0.7 - 0.5]	(0.5 - 0.4]	(0.4 - 0.3]	(0.3 - 0.1]
Homogeneous	AC + EF + B +D		EF + A +B +C +D	ABCDEF	A + B + C + D + E + F	
Heterogeneous	ABD + C + E + F	AB + EF + C + D	EF + A + B + C + D		ABCDEF	A + B + C + D + E + F

DISCUSSION

Based on the yield (Table 1) and the price data (Table 2), we could say that the component C_9 is a specialty. If the owner of process A wants to include specialty C_9 in his production, it is necessary to pass through the bottleneck of process C, where the potential profit is negative (Table 3). The module EF appears early as a solution, since it overcomes the negative point of process C. For the process F to show up in a module with process A, the investor needs to be willing to lower his profit expectations by 50% (Table 4). This result depends on the integration benefit. If the integration benefit is great enough, the module can be more profitable than the stand alone processes. For example the module AC appears in the set of strict solutions (α=1, no profit sacrifice). Even though process C has a negative profit potential, the module AC is profitable because of the integration benefit. Even though factor α is a continuous parameter, the final solution is discrete, and it appears with horizontal levels (Figure 2). This is because each solution comes as a combination of modules, so the potential solutions includes a set of "potential profit nodes".

CONCLUSION

Modularity level represents the number of processes integrated together. The modules can either be all the possible combinations amongst the processes or can be defined based on specific criteria. In this work the criterion was the ability to use the product of one process as a feed stream to another process. Modules take into account the value chain tree, but the combinations are automatically created without the need of a predefined superstructure. These modules are used for the synthesis problem. The results of the theoretical example show that non profitable processes can turn into profitable modules, depending on the integration benefit. Moreover, heterogeneity in the modular integration benefit leads to a higher profit potential and a wider variety of options. The deviation factor α deliberately lowers the profit potential in order to give a chance for some modules to emerge as potential integration solutions. Future work will deal with the cost and income estimation per module, the optimization of split fraction, and the uncertainty in material and product prices.

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