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Data-driven Optimization of Biomass Retrofitting Pathway to Empower Circularity for the Oil and Gas Transition

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The global effort to hasten the energy transition toward renewable energy challenged the major oil and gas (O&G) industry toward greener revolutionary changes. However, the complexity of the situation made the decision-makers contemplates to achieve a balance between economic and environmental sustainability. Circular economy (CE) is viewed as a potential alternative to pave a greener path for the O&G industry. In this work, retrofitting the O&G industry with biomass conversion technology is proposed to strategize toward a circular industry with the deployment of data-driven optimization approach. Multiple systematic analytical tools (e.g., multi-objective decision analysis (MODM), information entropy) are utilized to synthesize an optimal integration strategy. The developed model determines the optimal biomass retrofitting pathway by evaluating the performances (i.e., revenue, energy consumption, operating expenditure (OPEX), capital expenditure (CAPEX), carbon emissions) of various biomass conversion technologies. Based on the accumulated biomass technology data, the model assigns higher priority to CAPEX, (w_j = 0.2764), which has higher sensitivity to change compared to the other criteria (w_j = 0.2134 for carbon emissions, w_j = 0.2073 for energy consumption, w_j = 0.1824 for OPEX, w_j = 0.1206 for revenue). The developed model recommends pyrolysis as the optimal pathway given its greatest overall performance score of 91.44 % from TOPSIS. This paper demonstrates the use of data-driven optimization adapting Shannon entropy and TOPSIS to determine the optimal biomass retrofitting pathway for O&G industry towards circularity.

1. Introduction

The need for a global effort in the energy departure from fossil energy is emphasized during the 2021 United Nation Climate Change Conference (UN, 2021) amid the lack of achievement toward net-zero emission goal. Despite the undeniable pressure on the oil and gas (O&G) industry toward carbon neutrality goal, the indispensable economic contributions caused by the strong dependency on fossil source has stemmed into a problem of great complexity. While transition towards renewable energy is desirable, massive investments are required to foster the transition, which will have financial consequences on the business model (Marsh, 2022). This led to the decision-makers formulating a strategic transition plan to achieve balance between economic and environmental performance. The emerging trend of circular economy (CE) is a potential strategy to achieve the energy transition goal, which breaks away from the conventional end-of-line practice and shifts toward waste hierarchy management to ensure a closed-loop system (Prieto-Sandoval et al., 2018). This ultimately sustains the environment with reduced waste generation (Klemeš et al., 2021) and lowers the dependency on unrenewable raw materials by exploring bio-pathways within the O&G industry.

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In response to the increased expenditures and scarcity of resources, the integration of biomass conversion technologies into the existing O&G infrastructure is a potential solution toward the energy transition goal (Klemeš, 2013). Existing research on co-processing of biomass addresses the potential blend of bio-oil with vacuum gas oil (VGO) in terms of miscibility for co-processing in existing fluid catalytic cracking (FCC) units (Manara et al., 2018). Due to the presence of oxygenated compound in bio-oil, higher bio-oil quality derived using catalytic processes or hydrotreatment is generally preferable for co-processing to avoid increased coke formation and final product quality (Stefanidis et al. 2018). The economic attractiveness of biomass co-processing is evaluated with a supply-chain optimization model, which is dependent on the crude oil and bio-oil price gap (Zhang et al., 2022). While the economic feasibility of co-processing is explored, this work developes a systematic decision-making approach to evaluate both economic and environmental sustainability.
To date, there has been lack of literature that features strategic plans to integrate biomass into the conventional O&G business model and subsequently evaluates its sustainability performance in terms of economic and environmental aspects in the CE context. The novelty of this work is presented with the deployment of data-driven analysis to evaluate various potential biomass technology to be integrated into the existing O&G infrastructure to achieve CE. The adoption of Shannon entropy followed by Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) in this work was inspired by Teng et al. (2020) and aims to address the technology pathway decision-making process based on the inherited information accumulated through the literature database. A mathematical model is developed to identify the optimal technology pathway with the consideration of various performance criteria that cover both economic and environmental aspects. Therefore, the developed model aims to aid key industrial players and the decision-makers to establish a strategic plan to foster CE in O&G industry via the integration of biomass conversion technologies.

2. Problem Statement

The model formulated in this work aims to identify the optimal biomass conversion pathway to be integrated into the O&G industry. Figure 1 illustrates the superstructure of possible biomass technologies (e.g., pyrolysis, liquefaction, and gasification) that can be retrofitted into the downstream refinery. Note that empty fruit bunches (EFB) serve as the biomass feedstock in this work. The biomass technology data computed in the model consist of product yield (bio-oil (Y_{oil}), syngas (Y_{gas}), bio-char (Y_{char})), CAPEX (C_{CAPEX}), OPEX (C_{OPEX}), energy consumption (E_{energy}), and carbon emissions (E_{carbon}), which are summarized in Table 1.

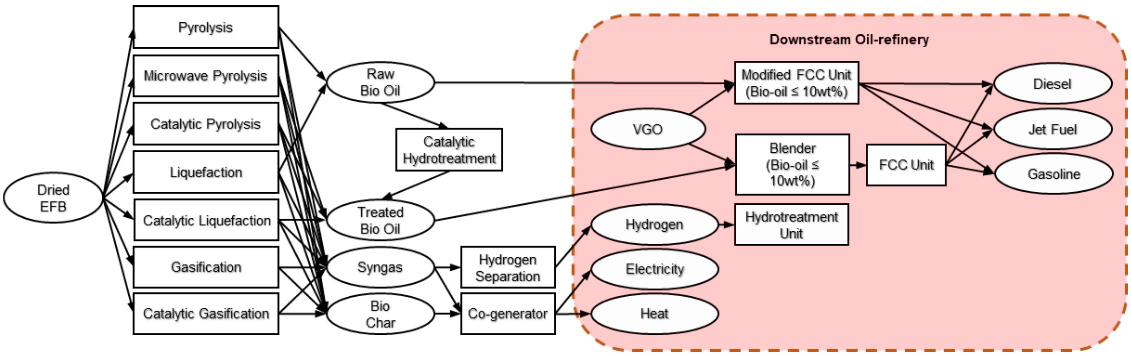

Figure 1: Superstructure of biomass conversion technology.

Table 1: Biomass conversion technology data (Cat. = Catalytic).

Technology	Y_{oil} [wt%]	Y_{gas} [wt%]	Y_{char} [wt%]	E_{energy} [kWh/t]	E_{carbon} [CO_2/t]	C_{CAPEX} [M$]	C_{OPEX} [$/t]	Reference
Pyrolysis	45.3	25.1	27.6	193.6	56.6	8.73	20.7	(Sulaiman and Abdullah, 2011)
Cat. Pyrolysis	36.0	30.0	33.0	212.1	62.3	8.73	21.7	(Ro et al., 2018)
Microwave Pyrolysis	38.3	26.6	35.1	405.0	150.4	8.7	52.9	(Idris et al., 2021)
Liquefaction	16.4	10.0	34.1	197.5	53.0	19.27	33.2	(Sangjan et al., 2020)
Cat. Liquefaction	19.0	-	-	167.3	44.7	19.27	33.2	(Nurul Suziana et al., 2021)
Gasification	-	81.0	10.0	442.2	131.1	8.63	20.7	(Lahijani and Zainal, 2011)
Cat. Gasification	-	75.0	10.0	357.6	105.8	8.63	21.4	(Mohammed et al., 2020)
Cat. Hydrotreatment	57.7	10.5	15.2	174.3	49.2	6.20	23.7	(Ly et al., 2019)

Co-processing of bio-oil in the existing downstream refinery is the core focus that fosters CE in O&G as it contributes to the production of various commodities (i.e., gasoline, diesel, jet fuel). As described by Lindfors et al. (2015), co-processing of bio-oil and vacuum gas oil (VGO) in the existing fluid catalytic cracking (FCC) unit can be easily implemented with minimal, if not zero modification to the FCC unit. Low bio-oil to VGO ratio (<10 wt%) is required to avoid detrimental effects on the process (i.e., increased coke formation, decreased product yield) due to the presence of oxygenated compound commonly found in bio-oil. Catalytic processes (i.e., catalytic pyrolysis, catalytic hydrothermal liquefaction) are generally preferred over non-catalytic counterparts for co-processing in FCC unit given the better attainable oil quality, which can have better storability and reduce equipment fouling due to lower content of oxygenated compounds and better stability (Stefanidis et al., 2018). The coke formation issue contributed to the low bio-oil quality is addressed with a modified FCC unit with a separate feeding system as proposed by Pinho et al. (2015). This opened out another potential pathway, which no longer requires additional catalysts uptake and bio-oil upgrading technologies (e.g., hydrotreatment upgrading). Hydrogen production technologies (e.g., steam reforming, membrane separation, etc.) are considered in the model since hydrogen is a valuable raw material in oil refining process (e.g., hydrotreatment, hydrocracking, etc.).

3. Methodology

Figure 2 describes the research flow deployed in this work. Prior to the modeling, technology information is collected through Scopus database. Based on the accumulated information, several performance criteria (i.e., revenue, energy consumption, OPEX, CAPEX, carbon emissions) of each biomass technology are formulated. As this established a multi-objective problem, Shannon entropy weight (Shannon, 1948) is adopted to determine the importance of each performance criterion. The entropy represents the variance within the dataset, which translates to importance when compared among the criteria. With the distributed weightage, TOPSIS (Hwang et al., 1993) is performed to rank the biomass integration pathways based on the relative closeness of each performance criterion. The developed model is expected to be capable of proposing the optimal biomass technology, which can be integrated into the O&G industry for better circularity.

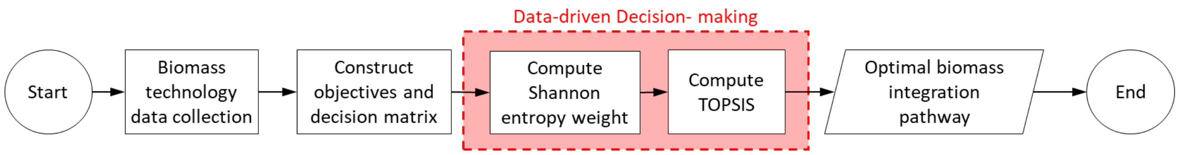

Figure 2: Research flowchart for data-driven optimization.

3.1 Shannon entropy-weight approach

The Shannon entropy-weight approach is dependent on the inherent information of the objectives, which avoids subjective factors contributing to the decision priorities. Eq(1) represents the Shannon entropy (E_j) for the respective biomass pathway (j). The normalized decision matrix $(\bar{X}_{ij})$ is used to ensure a uniform amplitude across all criteria (i). The entropy constant $-\frac{1}{\ln(m)}$ represents the maximum entropy of the system to ensure $0 \leq E_j \leq 1$ where, m refers to the number of possible biomass integration pathways (in this work, m = 23).

$$E_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} \bar{X}_{ij} \ln(\bar{X}_{ij}) \tag{1}$$

This enables the calculation of the inherent contrast intensity $(1 - E_j)$ where higher E_j signifies greater sensitivity to change, which equates to greater importance in decision priorities. The entropy-weight (w_j) can be computed using Eq(2), where n represents the number of criteria considered (in this work, n = 5).

$$w_j = \frac{1 - E_j}{n - \sum_{j=1}^{n} E_j} \tag{2}$$

3.2 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS evaluates and ranks the performance of respective pathways based on the Euclidean distance (or relative closeness) to the ideal solutions, while the criteria can be optimized differently (maximize if it is a beneficial attribute or minimize if it is a detrimental attribute). Prior to the computation of TOPSIS, the ideal best (V_j^{+}) and worst (V_j^{-}) solutions are formulated based on the individual criteria (i.e., highest profit, lowest cost) such that the imaginary solutions are established based on the preferred best and worst outcome. The Euclidean distances to the ideal best (t_i^+) and worst (t_i^-) solutions can be calculated such that the relationship between t_i^+ and t_i^- is inverse (see Eq(3) and Eq(4)):

$$t_i^+ = \sqrt{\sum\nolimits_{j=1}^{n} \left(\bar{X}_{ij} w_j - V_j^+\right)^2} \tag{3}$$

$$t_i^- = \sqrt{\sum\nolimits_{j=1}^{n} \left(\bar{X}_{ij} w_j - V_j^-\right)^2} \tag{4}$$

where, $\bar{X}_{ij}$ denotes the normalized decision matrix and w_j denotes the entropy weight. With the Euclidean distances, the respective pathway's performance (T_i) is calculated using Eq(5) and ranked to identify the optimal solutions. The integration use of entropy-weight and TOPSIS establish a data-driven decision-making model based on the inherited information without selective bias.

$$T_i = \frac{t_i^-}{t_i^+ + t_i^-} \tag{5}$$

4. Result and Discussion

Following the computed biomass technology data in Table 1, the generated Shannon entropy weight for the respective criteria is illustrated in Figure 3(a). Based on the outcome, the model tends to prioritize environmental criteria over economic. The distributed weightage signifies that CAPEX (w_j = 0.2764) has the highest priority followed by carbon emission (w_j = 0.2134), energy consumption (w_j=0.2073), OPEX (w_j = 0.1824), and revenue (w_j = 0.1206). This indicates that the environmental criteria have greater sensitivity to change compared to economic criteria with the exception of capital investment. Noting that the revenue criterion has the lowest priority, which is justified by its high dependency on the market condition that is generally less controllable by the decision-makers in most cases. Regardless of the inexpensive operating cost, profitability remains one of the key decision criteria and revenue still remains as one of the key considerations in this model.

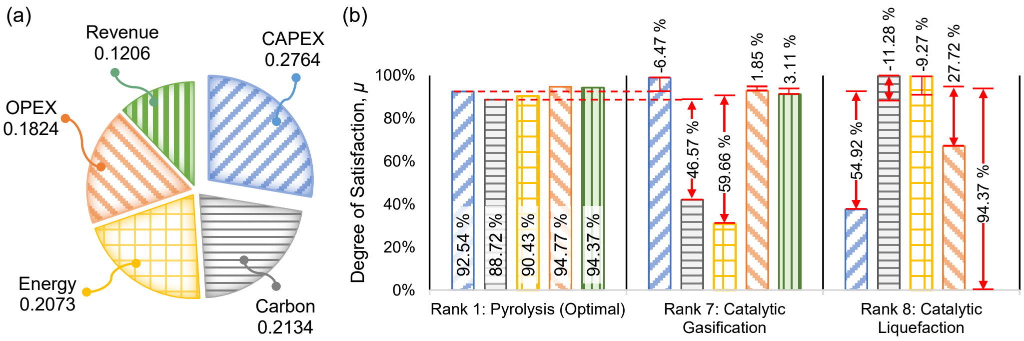

Figure 3: (a) Distributed Shannon entropy weightage; (b) Degree of satisfaction of respective decision criteria.

Based on the allocated weightages, various biomass pathways (23 pathways in total) are evaluated through TOPSIS, while the three conversion pathways (i.e., pyrolysis, gasification, liquefaction) are summarized in Table 2 with a perceivable favour towards pyrolysis route when compared to hydrothermal liquefaction and gasification. As illustrated in Figure 3(b), the model preferred pyrolysis route given its better degree of satisfaction (μ) for most decision criteria. The better performances of 54,92 % (CAPEX), 27.72 % (OPEX), and 94.37 % (revenue) in economic criteria with a relatively small environmental trade-off of 11.28 % (carbon emission) and 9.57 % (energy consumption) justify the favourability of pyrolysis over hydrothermal liquefaction route. Better improvements of 46.56 % (carbon emission), 59.66 % (energy consumption), 1.85 % (CAPEX), and 3.11 % (revenue) to most criteria with only 6.47 % deficiency in OPEX criteria signifying the superiority of pyrolysis over gasification. Figure 4 illustrates the preferred pyrolysis co-processing route with hydrogen produced from syngas consumed in the downstream facilities (e.g., hydrotreatment, hydrocracking, and etc.); while biochar is used as a boiler feed for power and heat generation, which can be used to sustain the biomass conversion technologies. The presented optimal solution is consistent with the literature expectation (Ramirez and Rainey, 2019), which views pyrolysis as more economical compared to gasification and liquefaction. This ensures the model reliability in determining the optimal solutions given a number of decision criteria without preferential bias.

Table 2: The top 10 solutions of respective biomass conversion routes.

Ranking	Overall Performance Score	Biomass Conversion	Bio-oil Pathway	Syngas Pathway
1	91.44 %	Pyrolysis	FCC-Modified[a]	Hydrogen Separation
7	66.01 %	Catalytic Gasification	-	Hydrogen Separation
8	59.31 %	Catalytic Liquefaction	FCC	-

[a]modified system where bio-oil and VGO are fed at different temperatures and locations (Pinho et al., 2015).

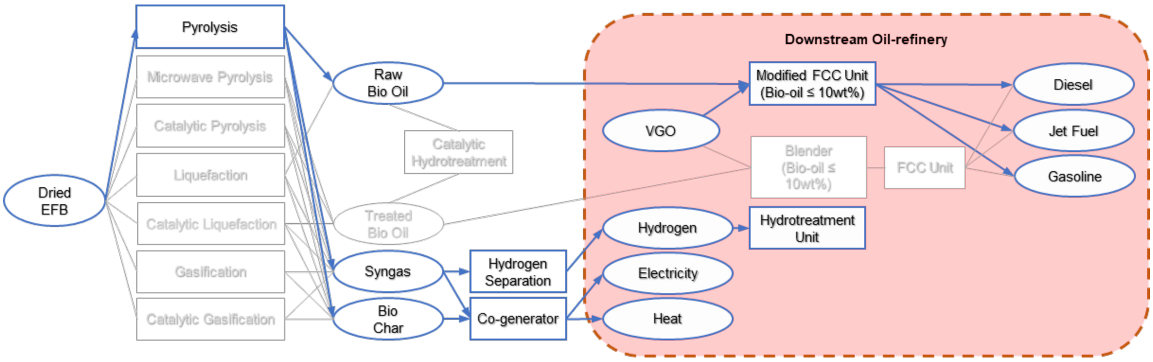

Figure 4: The optimal biomass integration route.

5. Conclusions

The novelty of this paper lies in the incorporation of data-driven analysis using Shannon entropy followed by TOPSIS to evaluate the various biomass integration pathway for O&G industry towards CE. The determined entropy weightage prioritizes the CAPEX criteria (w_j=0.2764) over the environmental (w_j=0.2134 for carbon emissions, w_j=0.2073 for energy consumption) with the exception of OPEX (w_j=0.1824) and revenue (w_j=0.1206). The model proposed the pyrolysis (91.44 %) route as the optimal solution in favour of the economic and environmental gains over the liquefaction (59.31 %) and gasification (66.01 %) routes. This demonstrates the solution's reliability to achieve the optimal trade-off between various decision criteria. The flexible nature of the developed model enables the ease of adapting new or modified technologies with the update to the accumulated technology database but is limited by the accuracy and availability of technology data (i.e., purchasing cost, material, and energy consumption) from literature, which requires comprehensive reviews. This work serves as guidelines for the decision-makers and researchers to evaluate and strategize the circularity of O&G industry by considering various biomass conversion pathways. The future work will extend toward various biomass feed and conversion routes (i.e., torrefaction, anaerobic digestion, hydrolysis, and etc.) to encompass a wider spectrum of conversion technologies into the model. Expansion toward macro perspective (i.e., supply-chain) enables the model to evaluate the regional supply and demand behaviour, which may influence the biomass integration decision. In the present work, the market condition is assumed constant throughout the project lifespan. The current model can be extended to cover stochastic modelling (Lo et al., 2021) so that the ever-changing market behaviour and supply chain uncertainties can be captured by the model.

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