CHEMICAL ENGINEERING TRANSACTIONS

VOL. 81, 2020

A publication of AIDIC

The Italian Association of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Petar S. Varbanov, Qiuwang Wang, Min Zeng, Panos Seferlis, Ting Ma, Jiří J. Klemeš

ISBN 978-88-95608-79-2; **ISSN** 2283-9216

DOI: 10.3303/CET2081101

Uncertainty Study of Empty Fruit Bunches-based Bioethanol Supply Chain

Shirleen Lee Yuen Lo[a], Jeremiah Jia Ler Choo[a], Karen Gah Hie Kong[a], Bing Shen How[a,*], Hon Loong Lam[b], Sue Lin Ngan[b], Chun Hsion Lim[c], Jaka Sunarso[a]

[a]Research Centre for Sustainable Technologies, Faculty of Engineering, Computing and Science, Swinburne University of Technology, 93350 Kuching, Sarawak, Malaysia
[b]The University of Nottingham Malaysia Campus, Department of Chemical Engineering, 43500 Jalan Broga, Semenyih, Selangor, Malaysia
[c]Universiti Tunku Abdul Rahman, Department of Chemical Engineering, Jalan Sungai Long, Bandar Sungai Long, Cheras, 43000 Kajang, Selangor, Malaysia
bshow@swinburne.edu.my

Throughout the years, researchers and key stakeholders of the industries have been pursuing sustainable development in industries. It can be in the form of green processing whereby it aims to minimize the environmental emissions, energy consumption and replace the usage of chemicals as raw materials. Many industry players substitute the usage of chemicals for greener raw material in support of the shift towards green processing. One of the processes that has adapted to this shift is the palm biomass-derived ethanol production. However, limited works had incorporated supply chain uncertainties into the techno-economic studies of bioethanol production. Therefore, this paper aims to evaluate the impact of biomass supply chain uncertainties on the techno-economic feasibility of palm-biomass derived bio-ethanol production. To achieve this, a stochastic mathematical model, known as Monte Carlo simulation is developed. This model can generate a financial probability curve that reflects on the various supply chain uncertainties. This probability curve can provide users and investors a bird's eye view of the potential losses induced by the uncertainties. A Sarawak case study is used to illustrate the effectiveness of the developed model that encompasses five supply chain uncertainties, such as bioethanol demand, bioethanol price, EFB price, EFB availability and transportation fuel price.

1. Introduction

Malaysia is one of the largest palm oil producers with an approximate total production of 39 % across the globe (Idris et al., 2012). According to Goh et al. (2010), Malaysia produced 47,402 kt/y, where only 10 % of it is extracted as oil whereas the rest becomes biomass residues with empty fruit bunches (EFB) comprising of 30.52 % of the biomass residues generated. Malaysia has high potential for usage of biomass feedstocks such as EFB due to the abundance of raw material and increasing awareness of key industry players towards sustainable development. The main principle of sustainability is catering to the needs of current requirement without affecting the usage of future generations (Klemeš et al., 2019a). Inefficient management of fossil fuels usage would lead to the environmental problems such as harmful gaseous emissions (Klemeš et al., 2019b). To date, researchers have widely studied the production of bioethanol from EFB as compared to other alternatives, include electricity and hydrogen (Table 1). According to International Energy Agency (2019), primary and secondary oil has remained as the largest share of energy supply from the year 1990 to 2016. The implementation of bioethanol can reduce the dependence on oil by substituting oil as biofuel. Bioethanol can act as an alternative fuel for petrol and gasoline given its comparable engine performance when it is being used as mixed fuel for transportation. Stochastic model is a type of mathematical model that produces a random probability-based distribution result based on the incorporated uncertainties and risks parameters (Kieffer et al., 2016). Uncertainties are known as variables that can fluctuate with time, which may significantly impact the financial outcome of the said supply chain. Additionally, the results obtained from stochastic optimization would

Paper Received: 30/03/2020; Revised: 28/05/2020; Accepted: 31/05/2020
Please cite this article as: Lo S.L.Y., Choo J.J.L., Kong K.G.H., How B.S., Lam H.L., Ngan S.L., Lim C.H., Sunarso J., 2020, Uncertainty Study of Empty Fruit Bunches-based Bioethanol Supply Chain, Chemical Engineering Transactions, 81, 601-606 DOI:10.3303/CET2081101

be closer to the real-world situation (Zakaria et al., 2020). As an exemplification, Ngan et al. (2020) had performed Monte Carlo simulation to evaluation the techno-economic feasibility of biomass supply chain. This method has been extended to evaluate the techno-economic feasibility of EFB-based bioethanol supply chain in this work. The scope of this supply chain comprises of transportation of EFB from harvesting site to bioethanol production plants and lastly the produced bioethanol will be transported to Kuching Port to be exported. The uncertainties to be incorporated into the Monte Carlo simulation are bioethanol demand, bioethanol price, EFB price, EFB availability and transportation fuel price. Then, the Monte Carlo model will be utilised to simulate the financial probability curve of the aforementioned supply chain for the users to evaluate.

Table 1. List of Products Generated from EFB (Bioethanol=B; Electricity=E; Hydrogen=H)

Author	B	E	H	Author	B	E	H
Gonzales et al. (2019)			✓	Kristiani et al. (2015)	✓		
Derman et al. (2018)	✓			Sari et al. (2015)	✓		
Han and Kim (2018)		✓		Tan et al. (2015)	✓		
Nurfahmi et al. (2016)	✓			Triwahyuni et al. (2015)	✓		
Dahnum et al. (2015)	✓			Sudiyani et al. (2013)	✓		
Do et al. (2015)	✓						

This study aims to demonstrate the usage of Monte Carlo model in evaluating the feasibility of EFB-based bioethanol supply chain.

2. Methodology

The methodology adopted in this research study was a four-step methodology. The first step of research began with the collection of data through both online and offline resources, which was used as an input for model development. The collected data (i.e., EFB data, fuel price historical data, logistic data, bioethanol data and, technology data) underwent data pre-processing (second step). The upper and lower boundaries for each uncertainty variable was determined. The mean and standard deviation was calculated for each variable using Eq(1) and Eq(2). The third step was model development that involves the development of Monte Carlo simulation model which incorporates various supply chain uncertainties. The fourth and final step was result analysis, where the respective detailed procedures are discussed in the following subsections.

$$\text{Mean, } \mu = \frac{(\sum X)}{n} \tag{1}$$

$$\text{Standard deviation, SD} = \sqrt{\frac{\sum(X-\mu)^2}{n-1}} \tag{2}$$

2.1 Model Development

The model was developed to evaluate the economic feasibility of EFB-based bioethanol supply chain with the incorporation of uncertainties. Net Present Value (NPV) was used as the economic indicator (Eq(3)):

$$\mathrm{NPV} = \sum_{n} \frac{(\mathrm{PV})}{(1+i)^n} \tag{3}$$

$$\mathrm{PV} = \mathrm{S^B} - \mathrm{C^{OP}} - \mathrm{C^T} \tag{4}$$

where PV refers to the present value (MYR), i refers to the interest rate (%), n refers to the number of interest periods (y). In general, PV encompasses four elements in the supply chain, i.e., sales of the bioethanol, $\mathrm{S^B}$, operating cost of the processing plant, $\mathrm{C^{OP}}$ (note that $\mathrm{C^{OP}}$ encompasses of biomass acquisition cost, material costs for consumed chemicals and required enzymes, wastewater treatment cost, and utility cost) and the transportation cost required in the supply chain, $\mathrm{C^T}$ (see Eq(4)). The equations were input into Microsoft Excel to formulate the Monte Carlo model.

3. Demonstration of Monte Carlo Model Case study

The objective of this case study is to demonstrate the usage of the developed Monte Carlo simulation model and ways of interpreting the results obtained from the developed model. Two Monte Carlo models are developed (i.e., for transportation cost evaluation and NPV evaluation) as shown in Figure 1. The transportation cost evaluation model will solely investigate one uncertainty that is fluctuation of transportation fuel price. This model aids in the selection of bioethanol production plant location(s). The model will be extended to further incorporated another four uncertainties; namely EFB price, EFB availability, bioethanol price and bioethanol demand). The extended model is used to evaluate the NPV of the supply chain. The NPV without consideration of uncertainties will also be calculated to evaluate the impact of uncertainties on the NPV.

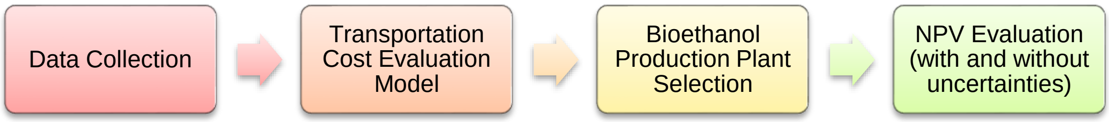

Figure 1: General Flow of Methodology for Case Study

A Sarawak case study is used. Kuching is selected as the main study area given its abundancy of oil palm biomass residues (Hamzah et al., 2019). Furthermore, Ta Ann Group Sdn Bhd situated at Serian, Kuching is selected as the source for EFB. The uncertainties for this study are shown in Table 2 along with their fixed value used when performing NPV calculations without consideration of uncertainties. The probability distribution used is normal distribution. The interdependence between each variable is not considered in this study. Three candidate locations are considered in this research (see Table 3). In order to minimize the transportation cost, the candidate location is situated between the palm oil mill to Kuching port. The specific distance and locations for all the three candidates processing are listed in Table 3 as extracted from Google Maps. All the necessities (i.e., power supply, water supply, labor and transportation infrastructure) has been taken into consideration during the selection of candidate locations.

Table 2: Uncertainty Variables

Variables	Unit	Lower Boundary	Upper Boundary	Fixed Value Used
EFB yield	t/y	11,335	14,399	12,867
Fuel Price	MYR/L	1.84	2.34	2.15
Bioethanol Price	MYR/L	3.385	4.754	4.2
Bioethanol Demand	kt	19.04	24.11	21.58
EFB Price	MYR/t	25.437	100.914	62.76

Table 3: Proposal of Potential Processing Plant

Plant	P_1	P_2	P_3
Longitude	110.5012	110.4751	110.5520
Latitude	1.1824	1.3107	1.4659
Distance from oil palm mill to plant (km)	18.6	42.8	80.4
Distance from plant to port (km)	78.5	41	24.2

4. Results and discussions

4.1 Processing plant location decision based on total transportation cost

Logistics management represents one of the major obstacles faced in biomass supply chain as higher logistics cost is required for the low-density and high-moisture biomass such as EFB (How et al., 2019). The selection of location for processing plant are selected based on the total transportation of each plant. The total transportation cost for the three processing plants P_1, P_2 and, P_3, with the incorporation of fuel price uncertainty. Monte Carlo simulation generates a random number for fuel price based on its mean and standard deviations and ultimately generate 1,000 different calculation results for total transportation cost. After performing the simulation, the mean transportation cost for Plant P_1, P_2, and, P_3 is MYR 177,424, MYR 131,069, and MYR 178,220. Figure 2 illustrates the Monte Carlo simulated results. It can be observed that the overall range for transportation cost is lower for Plant P_2 with a range of MYR 1.1 to 1.6 x 10^5. This is because the total transportation distance for P_2 is the shortest among the three and it is located between the oil palm mill and the port. The location of plant has approximately 78 % probability for a transportation cost of MYR 1.4 x 10^5. As mentioned by Kang et al. (2019), lower transportation cost is preferred as it would be able to reduce the operating cost and ultimately maximize the profit gained. As such, Plant P_2 is chosen due to its strategic location that minimizes the overall cost of bioethanol plant.

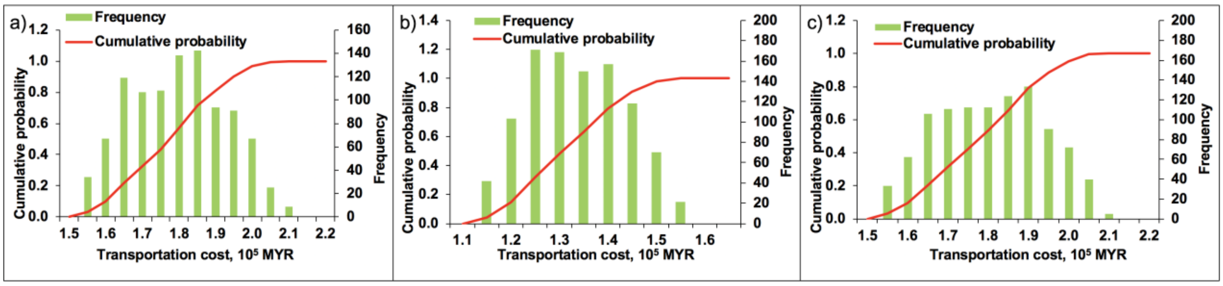

Figure 2: Monte Carlo Simulation Forecast for Total Transportation Cost of (a) Plant P_1, (b) Plant P_2, and (c) Plant P_3

4.2 NPV distribution

The NPV for bioethanol supply chain is evaluated using Monte Carlo simulation model. The model includes uncertainties such as transportation fuel price, EFB availability, EFB cost price, bioethanol demand and bioethanol pricing. The impacts of these uncertainties are modeled based on real-world statistical distribution. The lower and upper boundaries for the uncertainties obtained from statistical data are listed in Table 2. Other cost required for NPV evaluation includes total capital investment of the plant and the operational cost for bioethanol production. The total capital investment of the plant is MYR 2.52 billion. The capital investment cost includes equipment cost for pretreatment, saccharification and fermentation, chemical recovery, wastewater treatment, storage and utilities. Other parameters considered in capital investment are the land and building pricing, direct cost (i.e., warehouse, site development and additional piping) and indirect cost (i.e., project contingency, field expenses, office and construction fees and other costs associated with start-up business). The operational cost is calculated to be 2,204.6 $\pm$ 37.38 MYR/kL of bioethanol. The operating cost is an uncertainty in this evaluation since it encompasses various cost components, which fluctuate across the timeframe (e.g., EFB cost, transportation cost, and etc.). The Monte Carlo simulation was performed using Microsoft Excel. 10,000 iterations were performed due to the number of uncertainties incorporated that require longer stabilization time. The operating years of the bioethanol plant is assumed to be 20 y with an interest rate of 10 % annually (Humbird et al., 2011). The normal probability distribution of NPV for the bioethanol plant in this study is shown in Figure 3.

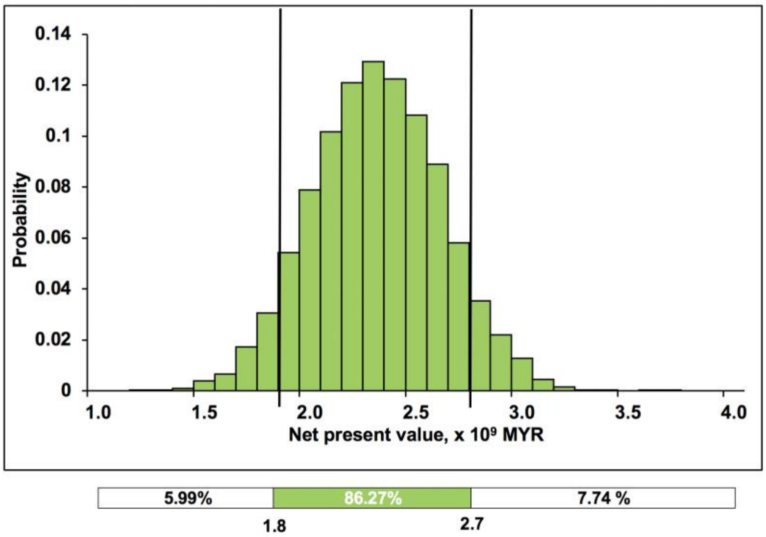

Figure 3: Distributions of NPV from Monte Carlo simulations

The mean NPV obtained from the Monte Carlo simulation is MYR 2.27 billion with a standard deviation of MYR 0.3 billion. For normal probability distribution, the values closer to the middle are most likely to occur. In this case, the NPV will be in the range of MYR 1.9 billion to MYR 2.7 billion with 86.27 % probability as seen in Figure 3. The NPV obtained without consideration of uncertainties (base case) is MYR 2.55 billion. The

comparison between the two approaches for NPV calculation showed an 11 % decrease in NPV when uncertainties are considered in the evaluation. The base case scenario is evaluated by assuming all the input variable such as fuel price, EFB availability, EFB price, bioethanol demand and bioethanol price are kept constant throughout the operational time of 20 y. The values used in the calculation of NPV without uncertainties consideration is shown in Table 2. It is less accurate to assume a constant value for evaluation as both incomes and expenditures are related to future periods and often subjected to fluctuation due to the uncertainties present (Gaspars-Wieloch, 2019). The variation observed in the mean NPV obtained is also caused by the differences in the incomes and expenditures of the bioethanol plant each year.
A comparison made between the difference in input variables for the base case and Monte Carlo simulation (see Table 4). Both the transportation cost and cost of EFB were found to be 2.02 % and 5.03 % higher as compared to the base case. Transportation cost and EFB cost are both included in the plant's operating cost. An increase in these two cost variables will lead to a decrease in NPV value that is consistent with the prior result obtained. The sale of bioethanol from Monte Carlo simulation is lower than that of base case scenario by 1.07 %. The sale of bioethanol presents the lowest impact on the NPV because of the small range of the statistical distribution of bioethanol demand obtained. Sales of bioethanol has greater dependence on the bioethanol demand. Higher demand implies higher sales volume resulting in greater profit obtained. This results in an overestimated profit analysis which may lead to unnecessary loss in future.

Table 4: Difference in income or expenditures between base case scenario and Monte Carlo simulation

Income/ Expenditures (MYR)	Uncertainty	Base Case (MYR)	Monte Carlo Simulation (MYR)	Percentage Difference (%)
Transportation Cost	Fuel Price	145,765.40	148,712.61	2.02
Cost of EFB	EFB Price	1,692,637.20	1,777,830.44	5.03
Sales of Bioethanol	Bioethanol Price	114,853,231.94	113,620,191.20	1.07

It can be deduced that uncertainties do affect the financial outcome of an investment. Without consideration of uncertainties, the financial outcome obtained will be idealistic, results in investors to be caught off guard when there are unexpected losses experienced in real life. In view of the above observations, it can be stated that Monte Carlo simulation that considers uncertainties in evaluating the economic feasibility of bioethanol production is more reliable and can hold a consultative (i.e., advisory) function in decision making for project investment.

5. Conclusions

As the economy for bioproducts such as bioethanol continues to grow, the industries targeting sustainable development will also face new challenges and opportunities. The status of economy is unpredictable, and the current status of economy cannot be used to predict the situation of the economy in the future. This research proposed analyzing the NPV of a supply chain network with the incorporation of uncertainties. The uncertainties are incorporated based on real world statistical distribution that allows closer replication of real-world scenarios. In this study, it was found that cost of EFB has a higher influence in the bioethanol supply chain as compared to other uncertainties studied. However, a limitation of this study is the impact of a particular uncertainty on the NPV is dependent on the range of statistical distribution. The approach used in this research can be used by relevant stakeholders in evaluating the profitability of their specific products, businesses or designs. The current proposed model can be further extended to incorporate the variation of biomass quality into the model. In fact, one of the concerns for commercializing biomass industry is biomass quality as expressed in carbon content, moisture content and so forth. To date, biomass quality has not been quantified into Monte Carlo model extensively.

Acknowledgements

The authors would like to acknowledge the financial support from Swinburne University of Technology (Sarawak Campus) via Research Supervision Grant [2-5545 RSG].

References

Dahnum D., Tasum S.O., Triwahyuni E., Nurdin M., Abimanyu H., 2015, Comparison of SHF and SSF processes using enzyme and dry yeast for optimization of bioethanol production from empty fruit bunch, Energy Procedia, 68, 107–116.

Derman E., Abdulla R., Marbawi H., Sabullah M.K., 2018, Oil palm empty fruit bunches as a promising feedstock for bioethanol production in Malaysia, Renewable Energy, 129, 285-298.
Do T.X., Lim Y-i., Jang S., Chung H-J., 2015, Hierarchical economic potential approach for techno-economic evaluation of bioethanol production from palm empty fruit bunches, Bioresource Technology, 189, 224–235.
Gaspars-Wieloch H., 2019, Project net present value estimation under uncertainty, Central European Journal of Operations Research, 27, 179–197.
Goh C.S., Tan K.T., Lee K.T., Bhatia S., 2010, Bio-ethanol from lignocellulose: Status, perspectives and challenges in Malaysia, Bioresource Technology, 101(13), 4834–4841.
Gonzales R.R., Kim J.S., Kim S-H., 2019, Optimization of dilute acid and enzymatic hydrolysis for dark fermentative hydrogen production from the empty fruit bunch of oil palm, International Journal of Hydrogen Energy, 44(4), 2191–2202.
Hamzah N., Tokimatsu K., Yoshikawa K., 2019, Solid fuel from oil palm biomass residues and municipal solid waste by hydrothermal treatment for electrical power generation in Malaysia: A review, Sustainability, 11(4), 1060.
Han J., Kim J., 2018, Process Simulation and Optimization of 10-MW EFB Power Plant, In: A Friedl, JJ Klemeš, S Radl, PS Varbanov, T Wallek (Eds.), Computer Aided Chemical Engineering, 43, Elsevier, 723–729.
How B.S., Ngan S.L., Hong B.H., Lam H.L., Ng W.P.Q., Yusup S., Ghani W.A.W.A.K., Kansha Y., Chan Y.H., Cheah K.W., Shahbaz M., Singh H.K.G., Yusuf N.R., Shuhaili A.F.A., Rambli J., 2019, An outlook of Malaysian biomass industry commercialisation: Perspectives and challenges, Renewable and Sustainable Energy Reviews, 113, 109277.
Humbird D., Davis R., Tao L., Kinchin C., Hsu D., 2011, Process design and economics for biochemical conversion of lignocellulosic biomass to ethanol, National Renewable Energy Laboratory, 01/01, 275-3000.
Idris S.S., Rahman N.A., Ismail K., 2012, Combustion characteristics of Malaysian oil palm biomass, sub-bituminous coal and their respective blends via thermogravimetric analysis (TGA), Bioresource Technology, 123, 581–591.
Kang K.E., Jeong J-S., Kim Y., Min J., Moon S-K., 2019, Development and economic analysis of bioethanol production facilities using lignocellulosic biomass, Journal of Bioscience and Bioengineering, 128(4), 475–479.
Kieffer M., Brown T., Brown R.C., 2016, Flex fuel polygeneration: Integrating renewable natural gas into Fischer-Tropsch Synthesis, Applied Energy, 170, 208–218.
Klemeš J.J., Varbanov P.S., Ocłoń P., Chin H.H., 2019b, Towards efficient and clean process integration: Utilisation of renewable resources and energy-saving technologies, Energies, 12(21), 4092.
Klemeš J.J., Varbanov P.S., Walmsley T.G., Foley A., 2019a, Process integration and circular economy for renewable and sustainable energy systems, Renewable and Sustainable Energy Reviews, 116, 109435.
Kristiani A., Effendi N., Aristiawan Y., Aulia F., Sudiyani Y., 2015, Effect of combining chemical and irradiation pretreatment process to characteristic of Oil Palm's Empty Fruit Bunches as raw material for second generation bioethanol, Energy Procedia, 68, 195–204.
Ngan S.L., How B.S., Teng S.Y., Leong W.D., Loy A.C.M., Yatim P., Promentilla M.A.B., Lam H.L., 2020, A hybrid approach to prioritize risk mitigation strategies for biomass polygeneration systems, Renewable and Sustainable Energy Reviews, 121, 109679.
Nurfahmi, Ong, H.C., Jan B.M., Tong C.W., Fauzi H., Chen W-H., 2016, Effects of organosolv pretreatment and acid hydrolysis on palm empty fruit bunch (PEFB) as bioethanol feedstock, Biomass and Bioenergy, 95, 78–83.
Sari A.A., Kurniawan H.H., Nurdin M., Abimanyu H., 2015, Decolorization of black liquor wastewater generated from bioethanol process by using Oil Palm Empty Fruit Bunches, Energy Procedia, 68, 254–262.
Sudiyani Y., Styarini D., Triwahyuni E., Sudiyarmanto, Sembiring K.C., Aristiawan Y., Abimanyu H., Han M.H., 2013, Utilization of biomass waste Empty Fruit Bunch Fiber of Palm Oil for bioethanol production using pilot–scale unit, Energy Procedia, 32, 31–38.
Ta Ann Holdings Berhad, 2018, 22nd Annual General Meeting Report <disclosure.bursamalaysia.com/FileAccess/apbursaweb/download?id=192961&name=EA_DS_ATTACHMENTS> accessed 9 November 2019
Tan L., Wang M., Li X., Li H., Zhao J., Qu Y., Choo Y.M., Loh S.K., 2015, Fractionation of oil palm empty fruit bunch by bisulfite pretreatment for the production of bioethanol and high value products, Bioresource Technology, 200, 572–578.
Triwahyuni E., Muryanto, Sudiyani Y., Abimanyu H., 2015, The effect of substrate loading on simultaneous saccharification and fermentation process for bioethanol production from Oil Palm Empty Fruit Bunches, Energy Procedia, 68, 138–146.
Zakaria A., Ismail F.B., Hossain Lipu M.S., Hannan M.A., 2020, Uncertainty models for stochastic optimization in renewable energy applications, Renewable Energy, 145, 1543–1571.