CHEMICAL ENGINEERING TRANSACTIONS
VOL. 70, 2018
A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet
Guest Editors: Timothy G. Walmsley, Petar S. Varbanov, Rongxin Su, Jiří J. Klemeš

ISBN 978-88-95608-67-9; **ISSN** 2283-9216
DOI: 10.3303/CET1870038

A Multi-Objective Optimization Model for the Design of a Biomass Co-Firing Supply Network

Jayne Lois G. San Juan[a,*], Charlle L. Sy[a], Raymond R. Tan[b]

[a]Industrial Engineering Department, De La Salle University, 2401 Taft Avenue, 1004 Manila, Philippines
[b]Chemical Engineering Department, De La Salle University, 2401 Taft Avenue, 1004 Manila, Philippines
jayne_sanjuan@dlsu.edu.ph

Because of increasing energy consumption, shrinking fossil fuel reserves, and climate change as an effect of greenhouse gas emissions, the interest in more sustainable and renewable sources of energy, such as biomass, has grown. Co-firing biomass with coal is an attractive alternative because it is an immediate and practical way to reduce coal usage and harmful emissions, requiring only minor modifications to the power plant. A multi-objective mixed integer non-linear programming model for a biomass co-firing network integrating biomass property considerations with investment, transportation and production planning is formulated and validated. A balance between the two conflicting objectives is achieved using a goal programming approach. Computational experiments reveal that biomass and coal blend ratios should be managed carefully to reach acceptable fuel properties. When improperly managed, it can negatively impact conversion yield and equipment life. Furthermore, less efficiency loss despite unsuitable feedstock properties encourage the model to use more biomass to replace coal because it will not negatively impact costs and would decrease pollutant emissions. Analysis also shows that pre-treatment facilities are prioritized depending on the effectiveness in improving properties that the biomass input violate the most based on power plant system requirements. Biomass seasonality as it impacts availability and quality are accounted for in purchase and storage planning, where purchases are done during periods when availability and quality is better, when low availability and quality are foreseen in succeeding periods, and the biomass are stored for future use. On the other hand, when quality and quantity of biomass does not experience significant seasonal changes, storage is avoided due to the damage it causes.

1. Introduction

Energy consumption worldwide has been rising, and is projected to increase approximately 30 % by 2040 (U.S. EIA, 2017). However, the reserves of fossil fuels (e.g. oil, gas, and coal), which are the main sources of energy, can only be found in a few countries and are expected to reach their limit soon; thus, creating a precarious energy supply (Iakovou et al., 2010). Aside from this, the production of energy from non-renewable sources causes health and environmental problems, such as climate change, associated with hazardous gas emissions (Ramos et al., 2018). Because of these, the interest in more sustainable and renewable sources of energy, such as biomass, has grown. It is considered to release net zero carbon emissions throughout its life cycle, and can potentially decrease dependency on fossil fuels.

The feasibility of using biomass, such as agricultural waste (i.e. rice straw), as an energy source for co-firing in modified existing coal power plants is acknowledged because it gives an immediate and practical mode of reducing coal usage and pollutant emissions, especially in areas where agricultural waste is abundant and improperly disposed. Furthermore, existing coal power plants with capacities of over hundreds of megawatts (MW) can be used instead of biomass-exclusive plants that only have less than 100 MW capacity (Madanayake et al., 2017).

Despite biomass being cheap itself, biomass supply chain management is critical to the economic feasibility of the system due to difficulties associated with seasonal and widely geographically dispersed availability and uncertain quality (Atashbar et al., 2016). Biomass and coal may be obtained from various sources, which impact the feed quality, transportation costs, and environmental emissions. Different source localities would entail

Please cite this article as: Juan J.L.G.S., Sy C.L., Tan R.R., 2018, A multi-objective optimization model for the design of a biomass co-firing supply network , Chemical Engineering Transactions, 70, 223-228 DOI:10.3303/CET1870038

variations in the fuel qualities influenced by the area's climate (Castillo-Villar et al., 2017). Biomass and coal properties must also be accounted for, along with the optimal blend ratios because blending fuels result in the blending of fuel properties (Veijonen et al., 2003). Changes in biomass properties along a biomass supply chain, specifically during storage, transport, and pre-treatment, must be considered to accurately determine feedstock amounts to source, transport, and use to satisfy energy demand. Not considering these variations and their impacts when modelling biomass co-firing systems can lead to decreased conversion throughput, shortened equipment life, significant long-term economic losses or increased environmental emissions (Castillo-Villar et al., 2017). Pérez-Fortes et al. (2014) cites bulk density, moisture content, lower heating value, and ash content as important fuel properties. Biomass typically has low bulk density, high moisture content, and low lower heating value. Bulk density impacts transportation and storage requirements, where low bulk density material would require more trips or higher capacity vehicles and facilities (Atashbar et al., 2016). According to Boundy et al. (2011), high moisture content decreases lower heating value, which is the basis for the amount of energy that may be produced from the feedstock. Ash content in the biomass feedstock gives rise to issues such as slagging and fouling that decreases the capacity and efficiency of the conversion equipment (Veijonen et al., 2003). Inherent biomass properties may be improved through pre-treatment, such as drying, pelletization, torrefaction, and pyrolysis among some, where each process betters the biomass properties by a certain extent (Atashbar et al., 2016).

However, previous studies that have considered multi-fuel blending ratios, such as Mohd Idris et al. (2018) and Griffin et al. (2014), overlooked the consideration of biomass properties. Pérez-Fortes et al. (2014) considered biomass properties in a pre-treatment process selection optimization model, but set required quality levels for the biomass output, which will serve as input to the power plant. The impact of fuel properties during combustion were not captured. Furthermore, multi-objective biomass co-firing optimization models proposed by Mohd Idris et al. (2018) and Griffin et al. (2014) solved each of the economic and environmental objectives separately as single objective optimization models. This cannot yield solutions that balances the trade-offs between conflicting objectives Savic (2002).

To date, no other study has been made that simultaneously optimizes economic and environmental objectives while incorporating the impact of feedstock properties on storage, transportation and pre-treatment requirements, conversion performance, and equipment degradation. The proposed model will decide whether each existing coal power plant must be retrofitted for co-firing, which would require capital investments that must be justified by the supply of biomass. For plants that are chosen for this investment, further decisions include the periods the co-firing option will be used, where and how much fuel feed must be sourced for each plant, as well as the optimal blends of biomass and coal for co-firing.

Table 1: Indices

Notation	Definition	Notation	Definition
i	Potential biomass supply locations	*l*	Existing coal power plants
j	Existing pre-treatment facilities	*t*	Time period in the planning horizon
k	Potential coal supply locations		

Table 2: Parameters and decision variables

Notation	Definition
d_t	Energy demand on time period t
lim_l^U	Upper coal displacement limit of coal power plant l
lim_l^L	Lower coal displacement limit of coal power plant l
bd_{it}^r	Bulk density of raw biomass from source i on period t
lhv_{it}^r	Lower heating value of raw biomass from source i on period t
mc_{it}^s	Moisture content of raw biomass from source i on period t
ac_{it}^s	Ash content of raw biomass from source i on period t
re_{lt}	Effectiveness of equipment repair in coal power plant l on period t
c_{lt}	Combustion capacity of coal power plant l on period t
e_{lt}^b	Biomass combustion efficiency in coal power plant l on period t
e_{lt}^c	Coal combustion efficiency in coal power plant l on period t
w_{ijt}	Amount of biomass transported from biomass source i to pre-treatment facilities j on period t
x_{jlt}	Amount of biomass transported from pre-treatment facilities j to coal power plant l on period t
y_{klt}	Amount of coal transported from coal source location k to coal power plant l period t
A_{lt}	Binary variable, 1 if coal power plant *l* is operating on period *t*

2. Model Formulation

The following section presents the model formulation for the biomass co-firing network described. A Mixed Integer Non-Linear Programming (MINLP) model was developed for the network, which aims to make investment and operational decisions that simultaneously minimizes the costs and environmental emissions of the network while satisfying demand and capacity constraints. The model also considers the impact of fuel properties on the efficiency and life of the conversion equipment. Table 1 and Table 2 show the indices, as well as the relevant parameters and decision variables used in the model.

2.1 Constraints

The demand for energy is applied in Eq(1). The amount of biomass and coal that undergo combustion multiplied by appropriate combustion efficiencies must be greater than or equal to demand. The inventory of biomass kept in the pre-treatment facilities is defined by Eq(2). This is equal to the amount of biomass carried from the previous period, plus the amount of biomass that were delivered from sources and have undergone pre-treatment, less the biomass transported to the coal power plants in the current period.

$$\sum_j \sum_l x_{jlt}\left(e_{lt}^b\right) + \sum_k \sum_l y_{klt}\left(e_{lt}^c\right) \geq d_t \qquad \forall t \tag{1}$$

$$I_{jt} = I_{jt-1} + nw_{jt} - \sum_l x_{jlt} \qquad \forall jt \tag{2}$$

Meanwhile, Eq(3) and Eq(4) sets upper and lower limits to the extent biomass will be allowed to displace the amount of coal processed in the power plants if the biomass co-firing option is activated. The biomass option may only be used if the coal power plant has undergone retrofitting.

$$\frac{\sum_j x_{jlt}}{\sum_j x_{jlt} + \sum_k y_{klt}} \leq lim_l^U O_{lt} \qquad \forall lt \tag{3}$$

$$\frac{\sum_j x_{jlt}}{\sum_j x_{jlt} + \sum_k y_{klt}} \geq lim_l^L O_{lt} \qquad \forall lt \tag{4}$$

Eq(5) and Eq(6) compute for the increased bulk density and lower heating value of biomass by multiplying the weighted average with the treatment efficiency respectively. Meanwhile, pre-treatment of biomass reduces its moisture content and ash content resulting in decreased total biomass weight as defined by Eq(7). The new moisture content is described in Eq(8) as equal to the total moisture after pre-treatment divided by the new total biomass weight.

$$\left(1 + bde_j\right) \frac{\sum_i bd_{it}^r w_{ijt}}{\sum_i w_{ijt}} = bd_{jt}^p \qquad \forall jt \tag{5}$$

$$\left(1 + hve_j\right) \frac{\sum_i lhv_{it}^r w_{ijt}}{\sum_i w_{ijt}} = lhv_{jt}^p \qquad \forall jt \tag{6}$$

$$\sum_i w_{ijt}\left(1 - mc_{it}^s - ac_{it}^s\right) + \sum_i w_{ijt}\left(mc_{it}^s\right)\left(1 - mce_j\right) + \sum_i w_{ijt}\left(ac_{it}^s\right)\left(1 - ace_j\right) = nw_{jt} \qquad \forall jt \tag{7}$$

$$\frac{\sum_i w_{ijt}\left(mc_{it}^s\right)\left(1 - mce_j\right)}{nw_{jt}} = mc_{jt}^p \qquad \forall jt \tag{8}$$

Eq(9) and Eq(10) computes the lower heating value and moisture content of the biomass and coal blend as a weighted average, and its underachievement and overachievement of the minimum lower heating value and maximum moisture content required by the technology in the power plants.

$$\frac{\sum_j lhv_{jt}^p x_{jlt}\left(1 - a_{jl}^{tp}\right) + \sum_k lhv^c y_{klt}}{\sum_j x_{jlt}\left(1 - a_{jl}^{tp}\right) + \sum_k y_{klt}} + lhv_{lt}^- - lhv_{lt}^+ = lhv_l^{min} \qquad \forall lt \tag{9}$$

$$\frac{\sum_j mc_{jt}^p x_{jlt}\left(1 - a_{jl}^{tp}\right) + \sum_k mc^c y_{klt}}{\sum_j x_{jlt}\left(1 - a_{jl}^{tp}\right) + \sum_k y_{klt}} + mc_{lt}^- - mc_{lt}^+ = mc_l^{max} \qquad \forall lt \tag{10}$$

The efficiency loss experienced by the coal power plant technology is a function of the underachievement of the minimum lower heating value, overachievement of the maximum moisture content of the biomass-coal blend, and the amount of biomass and coal processed by the machinery as in Eq(11). Eq(12) and Eq(13) defines the biomass and coal combustion efficiency of the current period as based on the previous period's efficiency less the efficiency loss if no repair is due, or as the original efficiency multiplied by repair effectiveness if repair was performed. Repair is performed when either efficiencies of biomass and coal combustion fall below a certain threshold.

$$el_{lt} = \beta\left[l\hbar v_{lt}^{-} + mc_{lt}^{+} + \sum_j x_{jlt} + \sum_k y_{klt}\right] \qquad \forall lt \tag{11}$$

$$\left(e_{lt-1}^{b} - el_{lt-1}\right)(1 - n_{lt-1}) + e_{l1}^{b}(re_{lt-1})n_{lt-1} = e_{lt}^{b} \qquad \forall lt \tag{12}$$

$$(e_{lt-1}^{c} - el_{lt-1})(1 - n_{lt-1}) + e_{l1}^{c}(re_{lt-1})n_{lt-1} = e_{lt}^{c} \qquad \forall lt \tag{13}$$

Similarly, the ash content of the pre-treated biomass in a pre-treatment facility is shown in Eq(14). Eq(15) computes the ash content in a coal power plant accounting for the mix of biomass and coal it received.

$$ac_{jt}^{t} = \frac{\sum_i w_{ijt}(1-a_{ij}^{tr})(ac_{it}^{s})(1-ace_j)}{nw_{jt}} \qquad \forall jt \tag{14}$$

$$ac_{lt}^{pp} = \frac{\sum_j ac_{jt}^{p} x_{jlt}\left(1-a_{jl}^{tp}\right)+\sum_k ac^{c} y_{klt}}{\sum_j x_{jlt}\left(1-a_{jl}^{tp}\right)+\sum_k y_{klt}} \qquad \forall lt \tag{15}$$

The amount of excess ash content from the allowable ash content level is defined in Eq(16). This is equal to the maximum between zero and the difference between the actual ash content of the feedstock and the allowable amount. With this, there will be no excess amount of the difference returned is negative. Eq(17) defines the percentage decrease in the coal power plant's combustion capacity because of the damage caused by excess ash content.

$$g_{lt} = \max(ac_{lt}^{pp} - ac_{l}^{allow}, 0) \qquad \forall lt \tag{16}$$

$$b_{lt+1} = b_{lt} + \lambda g_{lt} \qquad \forall lt \tag{17}$$

The model is also subject to capacity constraints associated with available supply in each of the biomass and coal source locations, as well as the pretreatment, storage, and combustion capacities each period. Bulk density becomes an input for storage and transportation requirements, especially in computing for the number of trips required two nodes, which incur the system costs and emissions per trip. Lastly, non-negativity, binary, and integer constraints apply to relevant variables.

2.2 Objective Function

The model seeks to maximize the performance of both objectives, which are to minimize total cost and environmental emissions; a balance is achieved by maximizing the smaller efficiency value to prevent optimizing one objective at the expense of the other as shown in Eq(18). Efficiency values are obtained by dividing the improvement achieved (difference between worst and actual values) and the potential improvement (difference between worst and potential values). Potential objective values are obtained by minimizing each corresponding objective as single objective optimization models. The worst value that the cost objective may take is its value when the environmental objective is optimized, and vice versa.

$$Max\ Z = min\left[\left(\frac{Cost_{max}-Cost}{Cost_{max}-Cost_{potential}}\right),\left(\frac{Env_{max}-Env}{Env_{max}-Env_{potential}}\right)\right] \tag{18}$$

The first sub-objective of the model is to minimize total costs incurred by the system. The total fixed cost is composed of costs obtained from retrofitting existing coal power plants, from operating coal power plants, pre-treatment facilities, from using the biomass option in modified power plants and storage areas in pre-treatment facilities. Variable costs include costs to purchase feedstocks, convert biomass and coal to energy, pre-treatment costs, holding costs, and transportation costs. Another sub-objective of the model is to minimize the system's environmental emissions, which is composed of pre-treatment emissions, combustion emissions, and carbon emissions from transportation activities.

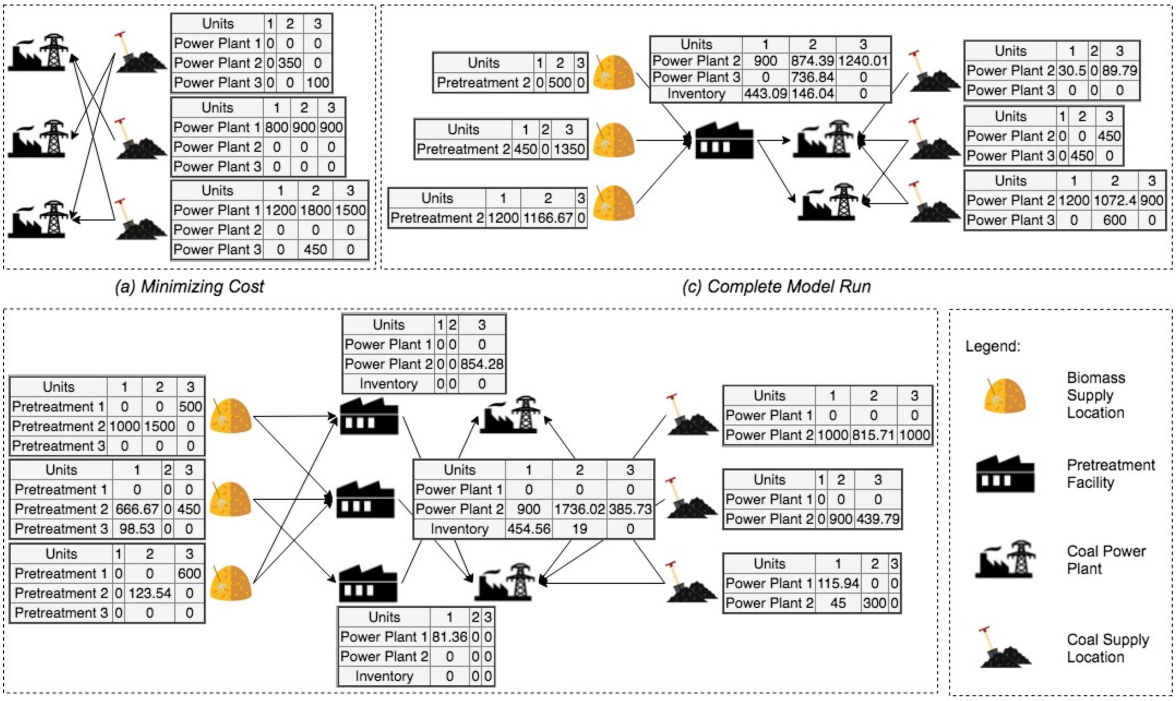
3. Computational Experiments

The model was validated using the nonlinear solver COUENNE in General Algebraic Modeling System (GAMS). The network considered includes 3 potential locations each for biomass sources, coal sources, pre-treatment/storage facilities, and coal power plants. Hypothetical values were used for the validation.

The results are presented in three parts, namely where each sub-objective is optimized separately, followed by the complete model run. Running the model wherein each objective is minimized individually is necessary to obtain the potential and worst values for cost and emissions needed in the full model run. The results are summarized in Figure 1, while the comparison of objective values is shown in Table 3.

Table 3: Comparison of cost and emissions objective performances

	Potential	Minimizing Cost		Minimizing Emissions		Complete Model Run	
			Efficiency		Efficiency		Efficiency
Cost	39,882.50	39,882.50	1	784,570.00	0	75,963.53	0.9515
Emissions	280,755.12	404,330.00	0	280,755.12	1	287,996.19	0.9414



(b) Minimizing Emissions

Figure 1: Model results

In minimizing the cost component separately, model results show a bias towards using only coal to satisfy the demand for energy as presented in Figure 1a. This is because coal is relatively cheap compared to biomass, especially when considering transportation requirements, storage requirements, and pre-treatment costs needed to handle biomass, and investment costs required to modify the existing coal power plants. Furthermore, using biomass, which has properties different from coal and from the machine specifications, decreases conversion efficiency more resulting in a need to purchase more feedstock to satisfy demand and for equipment repairs to be made. However, this sacrifices the environmental objective (Table 3).

On the other hand, when the environmental objective is optimized solely, more biomass is purchased and used by the system to prevent incurring the much larger emissions from coal firing. However, cost inflates significantly because of several reasons. Transporting biomass is relatively more expensive because of its inherent properties, the pre-treatment undergone by biomass also entail fixed and operating costs. Without regard for costs, the model chooses to open all the pre-treatment facilities depending on the pre-treatment process and effectiveness of each facility most suited to the initial quality of the biomass. In addition, the use of more biomass results in efficiency loss in the equipment leading to the purchase of more fuel to reach demand, and for the equipment to be repaired in period 2. This is why a sudden spike is seen in fuel use on the 2nd period, followed by a decrease by the 3rd period.

Optimizing each objective as single optimization models reiterate that a compromise must be found between the two conflicting objectives. One objective should not be minimized too much that no attention is given to the other. Considering only economic costs in optimizing the network result to a scheme where crucial investments and processes are disregarded to reduce costs, significantly compromising environmental sustainability. Similarly, when the system was optimized solely on environmental performance, costs are dramatically increased which may make the solution impractically expensive for long-term implementation. As shown in Table 3, simultaneously optimizing both objectives allow the system to reach efficiency ratings closer to each other. Figure 1c also show a more manageable network configuration. In an effort to control both costs and emissions, biomass is used by the system and one pre-treatment facility is opened. Less biomass is used compared to when only the emissions were optimized to control pre-treatment and transportation costs, equipment degradation and associated costs. In addition, only one pre-treatment facility is chosen to avoid the additional costs needed to operate more pre-treatment facilities. This required the model to choose the facility which costs the least to operate but resulted in the best improvements in biomass properties.

Biomass properties show to be a significant consideration in the modelling of biomass supply chains because it influenced network decisions across transportation, pre-treatment, storage, investment, and combustion activities. Specifically, costs and emissions increase with higher moisture content, higher ash content, lower heating value because of the additional transport trips, pre-treatment, and decreased combustion efficiency and capacity. When biomass properties and availability are relatively stable across periods, storage of the biomass is avoided because it causes deterioration and damage to the biomass. However, when biomass availability experience sudden dips, and biomass properties experience increased moisture content, for example during wet season, and increased ash content, purchases are done during earlier periods with sufficient quantity and appropriate quality and stored for future use.

4. Conclusions

A multi-objective multi-period mathematical model that incorporates the consideration of the impact of feedstock properties on storage, transportation and pre-treatment requirements, conversion performance, and equipment degradation in a biomass co-firing network was proposed in the study. A goal programming approach was used to simultaneously optimize two conflicting objectives – financial and environmental sustainability, allowing a balance between the two to be reached. Consideration of fuel properties shows that the use of biomass must be managed carefully because the difference of biomass quality and equipment requirements lead to efficiency loss and equipment degradation that could significantly affect overall system performance. Further analysis supports the importance of the efficiency loss rate in deciding on the amount of biomass to be used. When negligible efficiency loss occurs, more biomass is used. Damage due to storage is considered jointly with the seasonal biomass quality and quantity, where biomass is stored when there is insufficient supply and inappropriate quality, but is avoided when availability and properties are stable across periods. Future work can explore biomass availability and quality as uncertain parameters in a robust optimization model. In this study, it is assumed that retrofitting of coal power plants includes any required post-treatment technologies, such as flue gas treatment and heat recovery technology. Extensions to the study may include decisions on what post-treatment technology would be most appropriate to install.

References

Atashbar, N.Z., Labadie, N., Prins, C., 2016, Modeling and optimization of biomass supply chains: A review and a critical look, IFAC-PapersOnLine, 49, 604-615.

Boundy, R.G., Diegel, S. W., Wright, L.L., Davis, S. C., 2011, Biomass energy data book, Oak Ridge National Laboratory.

Castillo-Villar, K.K., Eksioglu, S., Taherkhorsandi, M., 2017, Integrating biomass quality variability in stochastic supply chain modeling and optimization for large-scale biofuel production, Journal of Cleaner Production, 149, 904-918.

Griffin, W., Michalek, J., Matthews, H., Hassan, M., 2014, Availability of biomass residues for co-firing in Peninsular Malaysia: implications for cost and GHG emissions in the electricity sector, Energies, 7, 12, 804-823.

Iakovou, E., Karagiannidis, A., Vlachos, D., Toka, A., Malamakis, A., 2010, Waste biomass-to-energy supply chain management: A critical synthesis, Waste Management, 30, 1860-1870.

Madanayake, B.N., Gan, S., Eastwick, C., Ng, H.K., 2017, Biomass as an energy source in coal co-firing and its feasibility enhancement via pre-treatment techniques, Fuel Processing Technology, 159, 287-305.

Mohd Idris, M.N., Hashim, H., Razak, N.H., 2018, Spatial optimisation of oil palm biomass co-firing for emissions reduction in coal-fired power plant, Journal of Cleaner Production, 172, 3428-3447.

Pérez-Fortes, M., Laínez-Aguirre, J.M., Bojarski, A.D., & Puigjaner, L., 2014, Optimization of pre-treatment selection for the use of woody waste in co-combustion plants, Chemical Engineering Research and Design, 92, 8, 1539-1562.

Ramos, A., Monteiro, E., Silva, V., Rouboa, A., 2018, Co-gasification and recent developments on waste-to-energy conversion: A review, Renewable and Sustainable Energy Reviews, 81, 380-398.

Savic, D., 2002, Single-objective vs. multi-objective optimisation for integrated decision support, 9th International Congress on Environmental Modelling and Software, 119, 7-12.

U.S. EIA, 2017, International Energy Outlook 2017 (DOE/EIA-0484(2017)), U.S. Energy Information Administration <www.eia.gov/outlooks/ieo/pdf/0484(2017).pdf> accessed 04.11.2017.

Veijonen, K., Järvinen, T., Alakangas, E., VTT Processes, 2003, Biomass co-firing - an efficient way to reduce greenhouse gas emissions, European Bioenergy Networks, Finland.