Optimal Design of Biomass Combined Heat and Power System Using Fuzzy Multi-Objective Optimisation

Citation for published version:
Asni, T & Andiappan, V 2021, 'Optimal Design of Biomass Combined Heat and Power System Using Fuzzy Multi-Objective Optimisation: Considering System Flexibility, Reliability, and Cost', *Process Integration and Optimization for Sustainability*, vol. 5, pp. 207–229. https://doi.org/10.1007/s41660-020-00137-4

Digital Object Identifier (DOI):
10.1007/s41660-020-00137-4

Link:
Link to publication record in Heriot-Watt Research Portal

Document Version:
Peer reviewed version

Published In:
Process Integration and Optimization for Sustainability

Optimal Design of Biomass Combined Heat and Power System using Fuzzy Multi-objective Optimisation: Considering System Flexibility, Reliability and Cost

Tommy Asni, Viknesh Andiappan*

School of Engineering and Physical Sciences, Heriot-Watt University Malaysia, 1, Jalan Venna P5/2, Precinct 5, 62200 Putrajaya, Wilayah Persekutuan, Malaysia

*E-mail: v.murugappan@hw.ac.uk

ABSTRACT

The increase in global energy demands has led to the need for efficient decarbonisation systems to produce renewable energy. One example of such system is the biomass combined heat and power (CHP) system. Biomass CHP systems have been gaining a lot of attention in the past few years. However, the variations of energy demand and biomass supply have created a challenge in synthesising flexible and reliable yet cost-effective biomass CHP systems. A system with high flexibility and reliability requires additional equipment that perform the same functions. The addition of equipment though, would increase the total cost of a biomass CHP system. In this respect, it is a challenge to synthesise a biomass CHP design with high flexibility, high reliability, and low cost. In this paper, a multi-objective fuzzy optimisation model was developed to synthesise the optimal design of the biomass CHP considering the system cost, flexibility, and reliability. Inspired by the reliability importance concept, this work expressed reliability linearly, unlike the complex and non-linear expressions developed in the past. Moreover, the changes of equipment performance under varying loads known as partial load performance is also considered. To demonstrate the proposed approach, a case study was conducted. The objective of the case study was to synthesise a CHP system using biomass from palm oil and wood mills as feed. Several scenarios with different power demand were solved to study the model performance. Additionally, the proposed linear model is compared to a model with non-linear expressions.

Keywords: Biomass, combined heat and power, system flexibility, system reliability, total cost, fuzzy optimisation

Nomenclature

Indices			
i	Index for biomass fuel	p	Index for product
j,j',jj'	Index for technologies	e	Index for energy

Parameters			
F_i	Available flow of biomass fuel	$C_j^{VAR,OPEX}$	Variable cost conversion for the operational expenditure of technology *j*
F_j^{MIN}	Minimum capacity of technology *j*	$C_j^{FIX,OPEX}$	Fixed cost constant for the operational expenditure of technology *j*
F_j^{MAX}	Maximum capacity of technology *j*	$C_{j'}^{VAR,OPEX}$	Variable cost conversion for the operational expenditure of technology *j'*
η_{ijp}^{FIX}	Fixed conversion of fuel *i* to product *p* through technology *j*	$C_{j'}^{FIX,OPEX}$	Fixed cost constant for the operational expenditure of technology *j'*
$\eta_{ijp}^{PARTIAL\ LOAD}$	Partial load conversion of fuel *i* to product *p* through technology *j*	$F_{e,BASE}$	Baseline output of energy *e*
PL_j	Partial load constant of technology *j*	$F_{e,CHANGE}$	Changes of energy *e* from baseline output
$F_{j'}^{MIN}$	Minimum capacity of technology *j'*	R_j	Reliability of technology *j*
$F_{j'}^{MAX}$	Maximum capacity of technology *j'*	$R_{j'}$	Reliability of technology *j'*
$\eta_{pj'e}^{FIX}$	Fixed conversion of product *p* to energy *e* through technology *j'*	$R^{MIN,SYSTEM}$	Minimum system reliability
$\eta_{pj'e}^{PARTIAL\ LOAD}$	Partial load conversion of product *p* to energy *e* through technology *j'*	RR_j	Relative reliability of technology *j*
$PL_{j'}$	Partial load constant of technology *j'*	$RR_{j'}$	Relative reliability of technology *j'*
$CF_j^{VAR,CAPEX}$	Variable cost conversion for the capital expenditure of technology *j*	C^{UPPER}	Upper limit for cost
$CF_j^{FIX,CAPEX}$	Fixed cost constant for the capital expenditure of technology *j*	C^{LOWER}	Lower limit for cost
$CF_{j'}^{VAR,CAPEX}$	Variable cost conversion for the capital expenditure of technology *j'*	FI^{UPPER}	Upper limit for flexibility index
$CF_{j'}^{FIX,CAPEX}$	Fixed cost constant for the capital expenditure of technology *j'*	FI^{LOWER}	Lower limit for flexibility index
AF	Annualising factor	RR^{UPPER}	Upper limit for relative reliability
R	Rate of return for payment period	RR^{LOWER}	Lower limit for relative reliability
n	Number of payment periods		
Variables			
F_{ij}	Flow of biomas fuel *i* to technology *j*	$C_{j'}^{OPEX}$	Operational expenditure of technology *j'*
I_j	Binary variable of technology *j*	C^{OPEX}	Total operational expenditure of the system
F_{jp}	Flow of output product *p* from technology *j*	C^{TOTAL}	Total cost of the system

F_p	Flow of product *p*	FI	Flexibility index
$F_{pj'}$	Flow of output product *p* to technology *j'*	$R_{jj'}$	Reliability of technology *jj'*
$I_{j'}$	Binary variable of technology *j'*	$I_{jj'}$	Binary variable of technology *jj'*
$F_{j'e}$	Flow of energy *e* from technology *j'*	R_{SYS}	Reliability of the system
F_e	Flow of energy *e*	RR^{TOTAL}	Total relative reliability
C_j^{CAPEX}	Capital expenditure of technology *j*	λ	Trade-off degree of satisfaction
$C_{j'}^{CAPEX}$	Capital expenditure of technology *j'*	λ^{COST}	Degree of satisfaction for cost
C^{CAPEX}	Total capital expenditure of the system	λ^{FLEX}	Degree of satisfaction for flexibility
C_j^{OPEX}	Operational expenditure of technology *j*	$\lambda^{RELIABILITY}$	Degree of satisfaction for reliabiility

1. Introduction

In the past few years, the growth of the world's population and the advancement of technologies have led to an increase in global energy consumption. To date, more than 80% of global energy consumption is met solely by fossil-based resources (BP, 2019). Studies have shown that by 2050, the oil and gas reserves are estimated to decrease to less than 20% (Martins et al., 2019). Aside from the depletion of non-renewable energy resources, the consumption of fossil-based resources also affects the environment greatly. Carbon dioxide (CO_2) and other greenhouse gases released through the combustion of fossil-based resources are the primary contributors to climate change and global warming. In 2018, around 38 billion tonnes of CO_2 are released from the consumption of fossil-based resources (Crippa et al., 2019). This amount has contributed to more than two-thirds of the total greenhouse gas emission in the world (Olivier and Peters, 2020). The excessive consumption of fossil-based resources has created both energy sustainability and environmental issues. With this in mind, policy-makers emphasise the need for a large-scale decarbonisation systems that operate on renewable energy sources.

Biomass combined heat and power (CHP) is an integrated system that generates electricity and thermal energy simultaneously from biomass fuel. As an energy source, biomass offers a number of potential environmental and economic benefits. For instance, a study by Koruba et al. (2017) pointed out that biomass gives environmental benefits because it produces low net CO_2 emissions as compared to fossil fuel energy sources. In addition, biomass residues that were previously regarded as wastes, can now be monetised to create economic benefits (Perea-Moreno et al., 2019). Biomass CHP systems also have higher energy conversion efficiency compared to conventional energy generation systems. The system converts biomass to gaseous product through gasifiers or anaerobic digestion systems. The gaseous product is further utilised to produce power and hot exhaust gas as the by-product. The heat from hot exhaust gas is then captured to produce utility like low pressure steam. Alternatively, biomass can be used in boilers to produce high pressure steam. The high pressure steam is then used to generate power.

Biomass CHP systems are required to be very versatile to generate heat and power. This is because energy demands are constantly changing due to the advancement of technologies and the increase of population. In this sense, biomass CHP systems need to be agile towards such changing demands. On top of this, the biomass fuel fed to the CHP system may have inconsistent compositions. This may affect the output of the biomass CHP system if not taken into account. In order to have a versatile system, biomass CHP systems must have high flexibility. From a technical point of view, a system can achieve high flexibility by increasing the number of technologies employed. However, this creates a challenge in designing a cost-effective biomass CHP system as systems with high flexibility would often require additional costs to increase the number of technologies in operation.

The challenge above can be addressed using mathematical optimisation. Mathematical optimisation can be defined as the process of maximising or minimising an objective function within a set of inputs under a certain degree of constraint (Andiappan, 2017). This optimisation approach starts by developing the mathematical model through formulating a set of mathematical equations, followed by solving the mathematical model. There are two elements in the process of developing a mathematical model: constraints and objective function (Arsham, 2014). Constraints within the mathematical model define the limits of variables. For example, the available amount of fuel, the allowable operating capacity, the amount of required product, etc. Meanwhile, the objective function is the criteria that the system needs to achieve. Normally it is either maximising or minimising of a certain aspect. Examples of the objective functions can be minimising total costs or maximising profit.

There are many mathematical optimisation studies related to the optimal design of biomass CHP system or multi-fuel CHP systems. For example, Zhang et al. (2015) developed an optimal design of a CHP-based microgrids considering environmental and economic sustainability aspect. The optimal design of the microgrids is developed using a multi-objective optimisation model. Wang et al. (2017) presented a mixed integer linear programming model to determine the optimal design and operation of CHP units based on the cost and carbon emissions. Elsido et al. (2017) used a mixed-integer non-linear programming and two-stage optimisation algorithm to determine the most profitable CHP units design with heat storage. Meanwhile, Chong et al. (2017) presented an approach to design a biomass energy system along with carbon capture technology. A systematic framework based on linear programming was developed by Ling et al. (2018) to design a biomass CHP system that can minimise the loss of economic opportunity due to varying energy demand. The model developed will determine the optimum biomass CHP design. Pérez-Uresti et al. (2019) developed a mixed-integer nonlinear programming model for the design of a renewable-based utility plant. The developed model is used to select the technologies with a minimum total system annual cost. From the studies shown in above, most of the work done on the optimal design development of the biomass CHP or CHP system with other types of fuel only considered the economic performance, environmental impact or both. Meanwhile, as mentioned previously, it is also necessary to consider the system flexibility due to the versatility nature of the biomass CHP system.

Flexibility is defined as the ability of the system to deploy its resources and assets to respond to the net demand changes (Lannoye et al., 2012). A system with high flexibility has the potential to avoid penalty costs caused by the uncertainties. One of the uncertainties in this case is the energy demand. Energy demand varies from time to time and is affected by various factors (e.g., changes in weather, increase of population, etc.). Even though system flexibility is important in the design of biomass CHP system, most of the studies on system flexibility optimisation is in the field of the manufacturing industry. For example, Song et al. (2016) integrated the discrete event simulation and the genetic algorithm in solving the optimisation problem in the flexible manufacturing system and Bhosale and Pawar (2018) modified a mathematical model to optimise the material flow of a flexible manufacturing system. Only until recent years, studies on energy system flexibility has been gaining more attention. There are some studies done on power system flexibility through the penetration of renewable energy sources. Alizadeh et al. (2016) did a review on additional flexibility requirements in power systems due to high penetration rate of renewables. Akrami et al. (2019) studied the change of power system flexibility in response to the penetration of renewables. A multiperiod mixed-integer linear model is formulated to design a flexible renewable-based utility plant (Pérez-Uresti et al., 2020). There are also some studies on optimising the flexibility of CHP system. For instance, Nuytten et al. (2013) proposed a generic model to assess the flexibility of CHP system. The model is used to determines the theoretical maximum flexibility of a CHP system coupled to a thermal energy storage. De Rosa et al. (2018) performed a techno-economic feasibility study on the gas turbine CHP system. The system is integrated with thermal and electrical storage and the energy flexibility potential response to the varying demand is studied. Results have shown that integrating the thermal energy storage system can save up to 7% of the cost. One notable study from Lok et al. (2020) did consider flexibility in the CHP system. However, the work from Lok et al. (2020) optimised the flexibility of an existing CHP system operation with respect to fuel emissions, start-up and shutdown costs. In fact, Lok et al. (2020) did not consider designing a CHP entirely. Similarly, Andiappan et al. (2017) developed a design operability and retrofit analysis framework for energy systems. In this work (Andiappan et al., 2017), a feasible operating range analysis was proposed to analyse the inherent flexibility of a highly integrated energy system that is in operation. Foong et al. (2019) later extended the work by Andiappan et al. (2017) to consider flexibility and utilisation factors for the design of a palm oil mill (Foong et al., 2018).

Other than flexibility, another challenge in the design of a cost-effective system is system reliability. Reliability is defined as the probability of a process or system to perform a required function for a certain time under a specified condition (Ebeling, 1997). Studies had shown that a system or process with low reliability often leads to undesirable consequences, such as safety issues, high costs of maintenance and repair (Paganin and Borsato, 2017). Thus, reliability should be considered in the initial design phase (Yang et al., 2011). In the past, reliability is often pre-determined based on heuristics or rule of thumb. For example, the n+2 rule where two additional units added to the initial proposed design. There are some studies done on the optimisation of system reliability. For instance, Haghifam and Manbachi (2011) studied the reliability of CHP systems and proposed a CHP reliability model. The model is based on the state space and the continuous Markov method. Ruiz-Rodriguez et al. (2014) presented a method based on shuffled frog-leaping algorithm and probabilistic load flow to optimise a biomass electric power system reliability. Sacaan et al. (2017) improved a power system reliability using an industrial strength compass algorithm. Andiappan et al. (2019) proposed a mixed integer linear program model to optimise the design and reliability of energy systems based on the function of equipment and their operating capacity. More recently, Benjamin et al. (2020) extended the a previously published work (Andiappan et al., 2018) to design a bioenergy park based on reliability.

In summary, many studies have looked to optimise the economic and/or environmental performance of the biomass CHP/CHP systems. However, there are only a few works done on optimising the reliability of the system along with system flexibility. However, aspects like flexibility and reliability are necessary to be considered in the design of the biomass CHP system. Low flexibility and reliability system would lead to additional costs during the operation. This is because a low flexibility and reliability system would require the addition of equipment or maintenance if there are any changes in energy demand or failure of equipment. To increase the system flexibility and reliability, it would also mean increasing the total costs. Therefore, a trade-off between cost and system flexibility and reliability need to be achieved. Cost, flexibility, and reliability are contradicting objectives, where improving one aspect would lead to sacrificing the other. Optimisation model that has two or more contradicting objectives also known as Multi-objective Optimisation (MOO). Optimisation contradicting objectives often generate a set of solutions, it is hard to satisfy all objectives with a single solution from the mathematical point of view (Cui et al., 2017). Study from Gunantara (2018) identified two methods of MOO that do not require complicated equations, which are Pareto and Scalarisation. Pareto method generated sets of solutions consisting of dominated solution and non-dominated solution. Meanwhile, scalarisation method converts multi-objective functions into a single solution using weights. Schmidt et al. (2019) applied the scalarisation method by developing a compact mixed-integer linear programming formulation, the problems are reduced to well-known single-objective problems. A review from Andiappan (2017) showed that there are two classes of approaches in obtaining a single solution for a MOO problem. Priori approaches and Posteriori approaches, two classes are distinguished by the time when the decision-maker provides additional preferences. Priori approach is before the solution process starts and posteriori approach is after the solutions generated. The weighted sum is one example of the priori approach. There are three commonly applied posteriori approaches ε-constraint, fuzzy optimisation, and EMOAs (evolutionary multi-objective algorithms).

The aim of this work is to develop a mathematical optimisation model to design a biomass CHP system with high flexibility, reliability, and low cost. Fuzzy optimisation, one of the posteriori approaches is chosen to optimise the design of the biomass CHP. The reason for this is because, unlike other techniques, fuzzy optimisation does not require prior knowledge from the decision-maker (Korte, 2003). In fact, fuzzy optimisation is employed to solve the fuzzy decision problem where a lot of uncertainties, ambiguity, and vagueness are involved. The working principle of fuzzy optimisation can be explained in 2 steps as shown in Fig. 1. The first step is the integration of the contradicting objective functions into one interdependence variable (λ). This interdependence variable (λ) represents the relations of the contradicting objectives. As mentioned previously, MOO model has two of more contradicting objectives. These contradicting objective functions can be classified into two types: Property to be maximised and property to be minimised. For objectives under the classification of property to be maximised, the higher the value of the higher the level of satisfaction. Meanwhile, it is the other way for objectives under the classification of property to be minimised. The second step would be the optimisation of interdependence variable (λ), when an interdependence variable (λ) of contradicting objectives is optimised, the result will generates an optimal solution with partial satisfaction of all the contradicting objectives.

Fig. 1. Working principle of fuzzy optimisation

Asides from this, this works also consider the partial load performance of the equipment in the biomass CHP system. This is because the variation of energy demand might cause equipment operating at partial load conditions (Karakurt and Güneş, 2017) and the performance of the equipment under partial load conditions might not be the same as the full load conditions. Some of the equipment performances are affected by the percentage of load capacity. For example, studies shown that the performance of a gas turbine is more sensitive to changes in load percentage compared to other equipment (Ebrahimi and Keshavarz, 2015a). Another study from Sarbu and Sebarchievici (2016) showed that the equipment efficiency is often lower when operates at lower loads than its rated capacity. Hence, the consideration of equipment partial load performance is important to measure realistic system performance when meeting energy demand variations.

This paper is divided into five sections. Section 1 is the introduction, Section 2 provides the methodology of the multi-objective optimisation approach developed in this work. Section 3 presents a case study conducted to demonstrate the model performance. Section 4 presents and discusses the result of the case study. Last, Section 5 draws on the conclusions of this work and some suggestions and recommendations on the directions for future work.

2. Methodology

As described previously, the aim of this work is to develop a mathematical optimisation model to design a biomass CHP system with high system flexibility, reliability, and low total cost. A generic superstructure of the biomass CHP is shown in Fig. 2. Several types of biomass fuels $i \in I$ is converted to products $p \in P$ through different process technologies $j \in J$. The products $p \in P$ will be further converted into energies $e \in E$ using various energy generation technologies $j' \in J'$. Some examples of the energies e produced are thermal energy (heat) and electrical energy (electricity).

Fig. 2. Generic superstructure for biomass CHP system

After the development of the biomass CHP superstructure, the next step is to formulate the mathematical equation. In this work, the mathematical equations can be classified into five different types. Starting from the mass and energy flow, cost, flexibility, reliability, and fuzzy optimisation. Each of the mathematical model formulation will be explained in detail in the following subsection. Note that there are two types of mathematical notations. Italic represents the variable determined by the model. Meanwhile, non-italic represents the fixed value defined in the model.

2.1 Mass Balance and Energy Conversion

There are many types of biomass fuel and technology options in a biomass CHP system. Different types of fuel may have different forms and compositions. For example, there are solid and liquid types of biomass fuel. Each type of fuel can be converted into different types of products depending on the technology selected. Meanwhile, each type of technology have their own respective performance, conversion, capacity limit, and specification.

The available biomass fuel flow F_i can be distributed to any process technologies j. F_{ij} is the flow of biomass fuel i to process technology j. However, not all of the available biomass fuel will be utilised, F_{ij} will be determined by the model. Eq. (1) represents the distribution flow of biomass fuels i to process technologies j.

$$\mathrm{F}_i \geq \sum_{j=1}^{J} F_{ij} \qquad \forall_i \qquad (1)$$

Each technology has operating capacity limits (i.e., maximum and minimum capacity limits). The flow of biomass fuel i to process technology j, F_{ij} must be larger than the minimum capacity F_j^{MIN} and lower than maximum capacity F_j^{MAX}. These constraints are shown in Eq. (2). Binary variable I_j represents the operational state (On = 1, Off =0) of technology j. It is introduced to ensure that Eq. (2) still valid when there is no flow to technology j.

$$\mathrm{F}_j^{MIN} I_j \leq \sum_{i=1}^{I} F_{ij} \leq \mathrm{F}_j^{MAX} I_j \qquad \forall_j \qquad (2)$$

In each process technology j, biomass fuel i is converted into product p. There are two types of conversion equations: Fixed efficiency performance and partial load performance equation. The classification of the conversion equation is based on the equipment performance. The fixed efficiency performance equation represents the conversion rate of equipment with a fixed efficiency. The performance of this type of equipment is only affected by the input flow. The fixed efficiency performance equation is shown in Eq. (3). η_{ijp}^{FIX} is the fixed conversion value of technology j and F_{jp} is the output flow of product p from process technology j.

$$F_{jp} = \sum_{i=1}^{I} F_{ij} \eta_{ijp}^{FIX} \qquad \forall_j \forall_p \qquad (3)$$

The second type of conversion equation is the partial load performance equation. As mentioned previously in the introduction section, the performance of some equipment is affected by its load percentage. For example, study from Karakurt and Güneş (2017) shown that the performance of a steam turbine reduced when operating at half of its maximum load. In this respect, the changes in equipment performance or efficiency based on load percentage is represented in Eq. (4). $\eta_{ijp}^{PARTIAL\ LOAD}$ is the partial load conversion value. $\mathrm{PL_j}$ is the partial load constant of process technology *j* and is often a negative value. $\mathrm{PL_j}$ is introduced to compensate for the changes in equipment performance due to operation under partial load conditions. Binary variable I_j is introduced in this equation to ensure that the partial load constant $\mathrm{PL_j}$ is only valid when process technology *j* is operating.

$$F_{jp} = \sum_{i=1}^{I} F_{ij} \eta_{ijp}^{PARTIAL\ LOAD} + \mathrm{PL_j} I_j \qquad \forall_j \forall_p \qquad (4)$$

There are many different types of products *p.* Some examples include biogas, syngas, steam, etc. The flow of the product under the same category will be collected and combined. Eq. (5) represents the flow combination of products *p*. F_p is the final combined flow of product *p* under the same category.

$$F_p = \sum_{j=1}^{J} F_{jp} \qquad \forall_p \qquad (5)$$

The combined flow of product *p* will then be distributed to different types of energy generation technologies *j'* shown in Eq. (6). Unlike the biomass fuel *i,* all the product converted will be distributed. $F_{pj'}$ is the flow of product *p* to energy generation technology *j'*.

$$F_p = \sum_{j'=1}^{J'} F_{pj'} \qquad \forall_p \qquad (6)$$

Similar to process technology *j,* each of the energy generation technology *j'* also have operating capacity limits. Eq. (7) presents the flow constraints or operating limits of energy generation technology *j'*. $\mathrm{F}_{j'}^{MIN}$ is minimum capacity and $\mathrm{F}_{j'}^{MAX}$ is maximum capacity of energy generation technology *j'*. The binary variable $I_{j'}$ represents the operational state (On = 1, Off =0) of the energy generation technology *j'*.

$$\mathrm{F}_{j'}^{MIN} I_{j'} \le \sum_{p=1}^{P} F_{pj'} \le \mathrm{F}_{j'}^{MAX} I_{j'} \qquad \forall_{j'} \qquad (7)$$

Energy generation technologies *j'* also have two different types of conversion equations. The fixed efficiency equation shown in Eq. (8) and partial load performance equation shown in Eq. (9). $\eta_{pj'e}^{FIX}$ is the fixed conversion value of energy generation technology *j'*, $\eta_{pj'e}^{PARTIAL\ LOAD}$ is the partial load conversion value of energy generation technology *j'*, and $\mathrm{PL}_{j'}$ is the partial load constant of energy generation technology *j'*. $F_{j'e}$ represents the flow of energy generated from energy generation technology *j'*. Binary variable $I_{j'}$ is introduced to ensure that the partial load constant $\mathrm{PL}_{j'}$ only valid when energy generation technology *j'* is operating.

$$F_{j'e} = \sum_{p=1}^{P} F_{pj'}\eta_{pj'e}^{FIX} \qquad \forall_{j'}\forall_{e} \qquad (8)$$

$$F_{j'e} = \sum_{p=1}^{P} F_{pj'}\eta_{pj'e}^{PARTIAL\ LOAD} + \mathrm{PL}_{j'}I_{j'} \qquad \forall_{j'}\forall_{e} \qquad (9)$$

The energy generated can be in many forms (e.g., heat energy, electricity energy, etc). The flow of same type of energy will be combined and the flow combination equation is shown in Eq. (10). F_e is the flow of the energy *e* from the entire system.

$$F_{e} = \sum_{j'=1}^{J'} F_{j'e} \qquad \forall_{e} \qquad (10)$$

2.2 Cost

Cost is one of the objectives considered in this work. The total cost includes the capital expenditure (CAPEX) and the operational expenditure (OPEX) of process technologies *j* and energy generation technologies *j'*. The cost the biomass fuel is not considered in this work. This is because most of the biomass fuels are waste or residue from various industries. For example, animal manure, wood waste, crop waste, etc. The CAPEX can be further divided into two types of costs, the variable cost and fixed cost. The variable cost is the cost of the equipment that varies based on the equipment capacity or size. On the other hand, the fixed cost is the cost of installing the equipment. The fixed cost is not affected by the equipment capacity and it is activated upon purchase of the equipment (i.e, when $I_j = 1$). Eq. (11) presents the capital expenditure of process technology *j*. C_j^{CAPEX} is the total CAPEX of process technology *j*. $\mathrm{CF}_j^{\mathrm{VAR,CAPEX}}$ and $\mathrm{CF}_j^{\mathrm{FIX,CAPEX}}$ represent the variable cost and fixed cost of process technology *j* CAPEX respectively. The binary variable I_j is introduced to ensure the fixed cost only valid when the process technology *j* is operating ($I_j = 1$).

$$C_j^{CAPEX} = \sum_{i=1}^{I} F_{ij}\mathrm{CF}_j^{VAR,CAPEX} + \mathrm{CF}_j^{FIX,CAPEX} I_j \qquad \forall_{j} \qquad (11)$$

Eq. (12) presents the capital expenditure of energy generation technology *j'*. $C_{j'}^{CAPEX}$ is the total CAPEX of energy generation technology *j'*. $\mathrm{CF}_{j'}^{\mathrm{VAR,CAPEX}}$ and $\mathrm{CF}_{j'}^{\mathrm{FIX,CAPEX}}$ represent the variable cost and fixed cost of energy generation technology *j'* CAPEX respectively. The binary variable $I_{j'}$ is introduced to ensure the fixed cost only valid when the energy generation technology *j'* is operating ($I_{j'} = 1$).

$$C_{j'}^{CAPEX} = \sum_{p=1}^{P} F_{pj'} \mathrm{CF}_{j'}^{VAR,CAPEX} + \mathrm{CF}_{j'}^{VAR,CAPEX} I_{j'} \qquad \forall_{j'} \tag{12}$$

Eq. (13) shows the total CAPEX equation. C^{CAPEX} is the summation of all the technologies CAPEX times annualising factor AF. Annualising factor AF is introduced to annualise total CAPEX. By doing so, the annual capital cost can be obtained. The calculation of annualising factor AF is shown in Eq. (14). R is the rate of return for payment period and the n is the number of payment periods.

$$C^{CAPEX} = \left(\sum_{j=1}^{J} C_{j}^{CAPEX} + \sum_{j'=1}^{J'} C_{j'}^{CAPEX} \right) \mathrm{AF} \tag{13}$$

$$\mathrm{AF} = \frac{\left[\mathrm{R}(1+\mathrm{R})^{n} \right]}{\left[(1+\mathrm{R})^{n} \text{-} 1 \right]} \tag{14}$$

Similar to the CAPEX, OPEX is also divided into two types of costs: The variable cost and fixed cost. The variable cost is the operational cost that varies based on the equipment flowrate. On the other hand, the fixed cost is the labour cost to operate the equipment. It is activated only when the equipment is operating (i.e., when $I_j = 1$). Eq. (15) shows the OPEX of process technology *j*. C_j^{OPEX} is the total OPEX of process technology *j*. $C_j^{VAR,OPEX}$ and $C_j^{FIX,OPEX}$ represent the variable cost and fixed cost of process technology *j* OPEX respectively. The binary variable I_j is introduced to ensure the fixed cost is only valid when process technology *j* is operating ($I_j = 1$).

$$C_{j}^{OPEX} = \sum_{i=1}^{I} F_{ij} \mathrm{CF}_{j}^{VAR,OPEX} + \mathrm{CF}_{j}^{FIX,OPEX} I_{j} \qquad \forall_{j} \tag{15}$$

Eq. (16) shows the OPEX of energy generation technology *j'*. $C_{j'}^{OPEX}$ is the total OPEX of energy generation technology *j'*. $C_{j'}^{VAR,OPEX}$ and $C_{j'}^{FIX,OPEX}$ represent the variable and fixed cost of energy generation technology *j* OPEX respectively. The binary variable $I_{j'}$ is introduced to ensure the fixed cost is only valid when energy generation technology *j'* is operating ($I_{j'} = 1$).

$$C_{j'}^{OPEX} = \sum_{p=1}^{P} F_{pj'} \mathrm{CF}_{j'}^{VAR,OPEX} + \mathrm{CF}_{j'}^{VAR,OPEX} I_{j'} \qquad \forall_{j'} \tag{16}$$

The total OPEX of the plant C^{OPEX} is the summation of all the technologies OPEX shown in Eq. (17).

$$C^{OPEX} = \sum_{j=1}^{J} C_{j}^{OPEX} + \sum_{j'=1}^{J'} C_{j'}^{OPEX} \tag{17}$$

The total cost of the system C^{TOTAL} is the addition of total CAPEX C^{CAPEX} and total OPEX C^{OPEX} shown in Eq. (18).

$$C^{TOTAL} = C^{CAPEX} + C^{OPEX} \tag{18}$$

2.3 Flexibility

Following total cost, another objective considered in this work is the system flexibility. Flexibility index *FI* variable is introduced to measure the flexibility of the CHP system towards the changes in energy demand. The flexibility index *FI* must lies within the range of 0 - 1 (shown in Eq. (19)). If *FI* equal to 1, it indicates that the system is flexible towards the changes in energy demand. Meanwhile, If *FI* equal to 0, It indicates that the system is not flexible and do not have the ability to adapt to the changes in energy demand. The third scenario is where *FI* lies in between 0 and 1, this indicates that the system is partially flexible towards the changes in energy demand (Swaney and Grossmann, 1985). Eq. (20) shows how flexibility index *FI* is determined. $\mathrm{F}_{e,BASE}$ is the baseline output of the energy *e,* whereas $\mathrm{F}_{e,CHANGE}$ is the changes of energy *e* from baseline output. Essentially, This would imply that the summation of $\mathrm{F}_{e,BASE}$ and $\mathrm{F}_{e,CHANGE}$ would be the total output of energy *e* from the system. For instance, consider that the intended power output of a CHP system is 10 MW. If the given system needs to be designed from scratch, then the $\mathrm{F}_{e,BASE}$ would be set to zero since there is no prior baseline output for a system that has not be implemented yet. Meanwhile, the $\mathrm{F}_{e,CHANGE}$ would be set to 10 MW. This will allow the decision-maker to determine if the system could be designed to achieve 10 MW via optimisation of *FI*. In this respect, if *FI* is found to be equal 1, then the system designed is highly flexible to achieve 10 MW. Anything less than 1, would indicate partial flexibility to 10 MW.

$$0 \le FI \le 1 \tag{19}$$

$$F_e = \mathrm{F}_{e,BASE} + \mathrm{F}_{e,CHANGE} FI \qquad \forall_e \tag{20}$$

2.4 Reliability

Along with cost and flexibility, system reliability was also considered in this work. The common practice in optimising the system reliability is through expressions that are non-linear as shown in Eq. (21). The non-linear reliability expressions calculate the system reliability based on the combination of series-parallel components. The series-parallel combination concept entails that reliabilities for all technologies in series to be consolidated to one value $\mathrm{R}_{jj'}$ for each pathway. The consolidated $\mathrm{R}_{jj'}$ value for each pathway is then used in Eq. (21) and is assessed as a parallel system. $I_{jj'}$ is the binary variable of respective technology *jj'*, and R_{SYS} is the system reliability.

$$R_{SYS} = 1 - \prod_{jj'=1}^{JJ'} (1 - R_{jj'} I_{jj'}) \qquad \forall_{jj'} \;, \quad \text{where } jj' = \{j, j'\} \tag{21}$$

In general, non-linear expressions of system reliability offer great accuracy, but it is more complex compared to linear expressions. Thus, it requires a large amount of time and effort to generate results (Silvia et al., 2016). Even though non-linear expressions have good performance, but it may not be suitable in a situation where a quick and less accurate result is required. For example, during the preliminary stage and to assist the decision making in synthesising the design of a plant. Thus, a linear approach is proposed as an alternative to the non-linear approach. The proposed linear approach was inspired by the reliability importance concept, which measures the effect of the change in reliability of each component compared to the system reliability

(Amrutkar and Kamalja, 2017). In this work, a variable essentially introduced to express relative reliability *RR*. The relative reliability *RR* variable is a normalised value, where the individual equipment reliability is compared to the minimum system reliability. A high equipment relative reliability *RR* indicates that the equipment reliability is higher and vice versa.

The relative reliability of process technology *j* is shown in Eq. (22). R_j is process technology *j* reliability, RR_j is the relative reliability of process technology *j,* and $\mathrm{R}^{\mathrm{MIN,SYSTEM}}$ is the system minimum reliability.

$$\mathrm{RR}_j = \frac{\mathrm{R}_j}{\mathrm{R}^{MIN,SYSTEM}} \qquad \forall_j \qquad (22)$$

Eq. (23) presents the relative reliability of energy generation technology *j'*. $\mathrm{R}_{j'}$ is the energy generation technology *j'* reliability and $\mathrm{RR}_{j'}$ is the relative reliability of energy generation technology *j'*.

$$\mathrm{RR}_{j'} = \frac{\mathrm{R}_{j'}}{\mathrm{R}^{MIN,SYSTEM}} \qquad \forall_{j'} \qquad (23)$$

The total relative reliability RR^{TOTAL} is calculated as shown in Eq. (24).

$$RR^{TOTAL} = \sum_{j=1}^{J} \mathrm{RR}_j I_j + \sum_{j'=1}^{J'} \mathrm{RR}_{j'} I_{j'} \qquad (24)$$

The total relative reliability RR^{TOTAL} is the summation of all the equipment relative reliability *RR*. It is used to represent the total system reliability. This is based on the theory of the higher amount of equipment operating the higher the system reliability. In reality however, this might not be the case, as system reliability can also be affected by the arrangement of the equipment in series/parallel. The linear approach of system reliability calculation would generate a less accurate result than the conventional non-linear reliability, but it is less complicated. The system reliability will be calculated manually after the optimal design of the biomass CHP is synthesised at the end.

2.5 Fuzzy Optimisation

As mentioned previously, fuzzy optimisation is used to solve the contradicting objectives in this work. Each of the contradicting objectives has its of respective degree of satisfaction. All the contradicting objectives are integrated into one degree of satisfaction λ and by optimising the degree of satisfaction λ, fuzzy optimisation can achieve a partial satisfaction of all the objectives. This is because fuzzy optimisation is based on a max-min aggregation rule, where the worst performance objective is maximised (Zimmermann, 1983,1978).

The trade-off between the contradicting objectives is achieved using equations from Eqs. (25) - (29).

$$\mathrm{C}^{\mathrm{UPPER}} - C^{TOTAL} / \mathrm{C}^{\mathrm{UPPER}} - \mathrm{C}^{\mathrm{LOWER}} = \lambda^{COST} \qquad (25)$$

$$FI - \mathrm{FI}^{\mathrm{LOWER}} / \mathrm{FI}^{\mathrm{UPPER}} - \mathrm{FI}^{\mathrm{LOWER}} = \lambda^{FLEX} \qquad (26)$$

$$RR^{TOTAL} - \mathrm{RR}^{\mathrm{LOWER}} / \mathrm{RR}^{\mathrm{UPPER}} - \mathrm{RR}^{\mathrm{LOWER}} = \lambda^{RELIABILITY} \qquad (27)$$

$$\lambda^{COST}, \lambda^{FLEX}, \lambda^{RELIABILITY} \geq \lambda \tag{28}$$

$$\text{Maximise } \lambda \tag{29}$$

C^{UPPER}, FI^{UPPER}, and RR^{UPPER} are the upper limits for cost, flexibility index, and relative reliability respectively. Meanwhile, C^{LOWER}, FI^{LOWER}, and RR^{LOWER} are the lower limits. The upper and lower limits of all the objectives are obtained by solving each objective individually. The lower limits of the flexibility index, relative reliability, and total cost can be obtained by minimising the total cost, C^{TOTAL}. The upper limits of the flexibility index and cost can be obtained by maximising the flexibility index, *FI.* The upper limit of the relative reliability can be obtained by maximising the total relative reliability, RR^{TOTAL}. λ^{COST}, λ^{FLEX}, and $\lambda^{RELIABILITY}$ are the degree of satisfaction for cost, flexibility, and reliability respectively. These degrees of satisfaction are illustrated in Fig. 3a-3c. The integration of contradicting objectives into a trade-off degree of satisfaction λ is shown in Eq. (28) and illustrated in Fig. 3d. Meanwhile, the trade-off λ is the maximised as shown in Eq. (29). By doing so, the optimal biomass CHP system design can be determined based on costs, flexibility and reliability.

The following section details the case study considered in this work. The case study was solved as a means of demonstrating the proposed methodology in Section 2.

Fig. 3. Types of degree of satisfaction (a = Cost, b = Flexibility, c = Reliability, and d = Trade-off)

3. Case Study

The objective of this case study is to demonstrate the proposed model by synthesising an optimal biomass CHP design based on different power demands, considering the trade-off between flexibility, reliability and cost. The types of biomass fuels considered in this case study are wastes from palm oil and wood mills. Table 1 presents the information of each fuel considered for this case study. The information includes the moisture content, available amount, calorific value, and the average size. In general, the biomass feed can be differentiated into two types: Solid and liquid types of biomass. In this case study, solid biomass fuel includes the palm kernel shell (PKS), palm mesocarp fiber (PMF), empty fruit bunch (EFB), and wood. On the other hand, palm oil mill effluent (POME) is classified under the liquid biomass fuel.

Table 1. Fuel information

In addition to Table 1, information on fuel compatibility is required. This is to assist in the development of the superstructure, whereby each type of fuel is connected to their respective compatible technologies. A list of various technologies considered in the biomass CHP system are shown in Table 2. There are different types of equipment considered under each technology. For example, a dryer is considered a technology. However, there are several types of dryers (i.e., rotary dryer, flash dryer, and superheated steam dryer) considered for drying purpose. Meanwhile, Table 3 presents the compatibilities of each fuel with their respective technologies.

Table 2. List of technologies considered

Table 3. Biomass fuel and technology compatibilities

Each type of biomass will require different types of pre-treatment processes. Biomass will then be converted into different types of intermediate products before being fed into the energy generation technology. In energy generation technology, power and heat will be produced depending on the types of technologies selected. Table 4 presents the process and energy generation technologies considered for selection in this case study, as well as the (intermediate) products and energies generated from different type of biomass fuels.

Table 4. Possible technologies, products and energies for different type biomass fuels

The process technologies shown in Table 4 includes pre-treatment. The pre-treatment process of the solid biomass fuel involves shredding and drying processes. After pre-treatment of solid biomass, there are two types of technologies used to convert the solid biomass: Boilers and Gasifiers. Boilers are used to convert solid biomass fuel to steam and gasifiers are used to convert solid biomass fuel to syngas. The liquid biomass fuel POME can be converted into the biogas. The pre-treatment process of the biogas in this case is the separation of impurities in the biogas (carbon dioxide, carbon monoxide, etc). There are five different options for the separation of gas impurities (refer to Table 2). Aside from this, there are three different possible intermediate products converted from solid and liquid biomass fuels. These intermediate products include steam, syngas and biogas. Produced steam is only compatible with specific types of energy generation technologies like steam turbines and stirling engines. Meanwhile, syngas and biogas can be fed into either a gas turbine integrated with a heat recovery steam generator, gas engine, or micro-turbine engine. The properties of intermediate products and steam considered for this case study is shown in Table 5.

Table 5. Intermediate Products and steam properties

Combining all the information of the biomass fuels and their respective technological compatibilities of fuels and technologies, a superstructure is developed as shown in Fig. 4. Following the development of the superstructure, a mixed-integer linear programming (MILP) model is developed using Eqs. (1) – (29) shown previously in Section 2. Next, the information on each technology is collected. Table 6 presents the data of the specifications of each technology. Note that the reliability data included in Table 6 represent the values for R_j used in Eqs. (22) – (23) to define the relative reliability.

The model developed in this case study, is then solved in four scenarios. Each scenario contains a different power demand (i.e., 5 MW, 10 MW, 15 MW, and 20 MW). However, these four scenarios (i.e., Scenarios 1-4) all have a constant heat demand (i.e., 1 MW). The purpose of this is to analyse the implications of different power demands on the trade-off between cost, reliability and flexibility. In addition to that, these four scenarios focused on the grassroots design of the biomass CHP system. Therefore, the $F_{e,BASE}$ of all scenarios are set to be zero and the $F_{e,CHANGE}$ of each scenario are their respective power demands (5 MW, 10 MW, 15 MW, and 20 MW). The MILP model was developed using LINGO v18.0 (ASUS A45V laptop with Intel Core i7 (2.40 GHz) processor and 12.0 GB RAM). The model consists of total 513 variables, 43 integer variables, and 521 constraints. The duration used to solve the model is within 3 seconds. An additional scenario (i.e., Scenario 5) was solved, but this time with a non-linear model. The non-linear model was built using typical non-linear expressions for system reliability

(Refer to Eq. (21)) was also developed. The performance of the proposed linear model will be compared to the non-linear model. This is shown in the fifth scenario of the case study.

Fig. 4. Case study biomass CHP superstructure

Abbreviations for Superstructure

Table 6. Technology specification data

4. Results and Discussion

In this section, the results for all five scenarios considered in the case study are presented and discussed. In each scenario, fuzzy optimisation was used to determine the optimal design based on a trade-off between cost, flexibility and reliability. To solve the fuzzy optimisation model, upper and lower limits for each objective are required. These limits were obtained using the steps mentioned in Section 2. A summary of the upper and lower limits can be found in Table 7. As mentioned, Scenarios 1-4 employed the linear expressions shown in Eq. (22)-(24) for system reliability. The values obtained via Eqs. (22)-(24) were then translated into system reliability using conventional reliability expression shown in Eq. (21). Meanwhile, the system reliability in Scenario 5 was generated directly from the non-linear model. Lastly, the commonly selected technologies among all scenarios are identified and these technologies are classified under different categories based on the number of appearances.

To solve a fuzzy optimisation model, the upper and lower limits of each objective are required. This was shown in Eqs. (25)-(27) where the upper and lower limits obtained are used to calculate the degree of satisfaction of each objective. Table 7 presents the upper and lower limits obtained for each objective in all the five scenarios.

Table 7. Upper and lower limits of objectives

4.1 Scenario 1 : Power Demand of 5 MW

In Scenario 1, a power demand of 5 MW was considered. Fig. 5 presents the optimal biomass CHP system design to produce 5 MW, taking into consideration of the total cost, flexibility and reliability. The results showed that all the available feed was not completely utilised in the optimal biomass CHP design. Instead, only a certain portion of each type of fuel was utilised.

Fig. 5. Scenario 1 optimal biomass CHP design

For instance, palm kernel shell (PKS) is not selected in Scenario 1. When compared to other types of fuel, PKS has the lowest available amount of biomass fuel. Reducing the type of biomass fuel would also lead to a reduction in the variety of technologies selected. This would also result in a lower total cost. Meanwhile, all three types of dryers were chosen. By doing so, the system reliability is greatly increased, but for the technology used to convert the biomass fuel to the product, only boilers technologies were selected. This is because of the cost and the size of technology demand. The gasifiers have higher efficiency but also higher capital and operational cost. Moreover, the energy generation technologies compatible with gasifiers (refer to Table 3) are more suitable for large scale operation. These types of energy generation technologies also have a minimum operating capacity. With a relatively low power demand in Scenario 1 (5 MW), these types of energy generation technologies were not feasible.

Meanwhile, in the liquid biomass fuel process, pressure swing adsorption (PSA) and membrane separator (MS) were selected for the purification process of the produced biogas. Compared to other types of technology, PSA and MS units have relatively good efficiency and very high reliability. In addition, MS unit is more suitable for smaller-scale operation because of its low operating capacity. Moreover, all three of the energy generation technologies were selected (i.e., gas turbine (GT2), gas engine (GE2), and micro-turbine engine (MT2)). Conventionally, only one technology would be required to generate that small amount of power demand. However, by increasing the number of technologies operating in parallel, this would increase the system reliability.

The total power produced in the system is around 4.94 MW. The system did not achieve the power target completely but was able to meet most of it. This means that a considerably high system flexibility of 0.99 was achieved. The system reliability reached 0.986, thus, both system flexibility and reliability attained were very high. However, the degree of satisfaction of the system was just 0.65. This can be concluded that cost is the least satisfied objective out of the three in Scenario 1.

4.2 Scenario 2 : Power Demand of 10 MW

For Scenario 2, the optimal biomass CHP design for the power demand of 10 MW is shown in Fig. 6. Unlike Scenario 1, in Scenario 2 all biomass fuels were chosen. However, all biomass fuels were partially utilised in this scenario except for PKS. In the solid biomass process route, two types of dryers were selected. Superheated steam dryer (SSD) was not chosen because of its high capital and operational costs. The reliability of the SSD unit is also lower compared to the other two types of dryers. Meanwhile, two different boilers types (i.e., stoker boiler (SB) and fluidised bed boiler (FBB)) and the fluidized bed gasifier (FBG) were selected. The addition of the FBG unit from Scenario 1 is caused by the increase of power demand and biomass fuel flow. FBG unit is selected rather than the fixed bed gasifier (FXBG) because the FBG unit has a higher efficiency and reliability. Similar to Scenario 1, steam turbines (i.e. high pressure steam turbine (HPST) and medium pressure steam turbine (MPST)) and stirling engine (SE) were selected as the energy generation technologies to produce steam. For the syngas product, GE1 and MT1 units were selected. The GT1 unit has a much higher minimum capacity compared to GE1 and MT1 units. Although the GT1 unit has a higher efficiency compared to GE1, but its reliability is lower than GE1 unit.

Fig. 6. Scenario 2 optimal biomass CHP design

For the liquid biomass fuel, the amount of flow required is the same as Scenario 1. However, the technologies chosen in Scenario 2 were different to Scenario 1. Water scrubber (WS) and MS units were selected instead. This is because the addition of other types of technologies in the solid biomass fuel processes had already increased the system reliability to the desired value. Hence, WS unit which has higher efficiency, lower cost, and lower reliability is chosen instead of PSA unit.

In Scenario 2 , the system reliability was increased to 0.991 and the system flexibility decreased to 0.89 compared Scenario 1. Meanwhile, even though the power demand in Scenario 2 is higher than Scenario 1, the total cost of the system generated in Scenario 2 was slightly lower than in Scenario 1. Thus, it can be concluded that the total cost objective in Scenario 2 was the most satisfied objective compared to the other two objectives. The result also showed that the degree of satisfaction in Scenario 2 is higher compared to Scenario 1.

4.3 Scenario 3 : Power Demand of 15 MW

Fig. 7 presents the optimal biomass CHP design for Scenario 3 with the power demand of 15 MW. In Scenario 3, the increase of power demand led to the increase of biomass fuel flow. All the biomass fuel except empty fruit bunch (EFB) were utilised to their maximum available feed flow. This is because EFB has a lower calorific value compared to PKS and palm mesocarp fiber (PMF). Even though the calorific value of EFB is higher than wood fuel, the available amount of wood is lower than EFB. However, the available amount of EFB is not enough to supply the remaining required solid biomass fuel after utilising the PKS and PMF fuels. Hence, wood fuel was fully utilised first and the remaining amount was supplied with EFB. The solid biomass fuel pathway in Scenario 3 was the same as Scenario 2.

Fig. 7. Scenario 3 optimal biomass CHP design

In the liquid biomass pathway, the PSA unit was chosen over the MS unit. This is because of the increase of the liquid biomass feed flow to the system. As mentioned previously in Scenario 1, MS unit is suitable only for smaller scale operation. Thus, the increase of the feed flow led to choosing the PSA unit instead. The efficiency of the PSA unit is lower and it cost more compared to MS unit. However, the reliability of the PSA unit is much higher compared to the MS unit. In fact, its operating capacity is much larger than the MS unit. Hence, a combination of PSA and WS units was selected for larger scale operation of biogas.

The system reliability in Scenario 3 is higher than in Scenario 1 and 2, but the flexibility decreased slightly from Scenario 2, even though Scenario 3 and Scenario 2 share an almost identical technologies arrangement. This is because of the distribution of syngas to the gas engine (GE2). Flexibility was also affected by the total heat generated. The heat demand of every case study is 1 MW and the only source of heat generation in Scenario 3 is through the heat recovery steam generator (HRSG2) that is integrated with gas turbine (GT2). Compared to Scenario 1 and 2, the distribution of syngas to GT2 and HRSG2 units in Scenario 3 is lower than to GE2 unit. Because of this, the total heat generated in Scenario 3 is lower than in Scenarios 1 – 2. As a result, the system flexibility was reduced in this scenario. The total cost in Scenario 3 is higher than Scenario 2. This is valid because the capital cost of the equipment increases as the size or capacity of the operation. In Scenario 3, all three objectives have equal trade off. However, the trade-off degree of satisfaction decreases compared to Scenario 2.

4.4 Scenario 4 : Power Demand of 20 MW

In Scenario 4, the power demand is 20 MW. Fig. 8 presents the optimal design of biomass CHP for Scenario 4. The configuration in Scenario 4 is relatively similar to Scenario 3. The only difference is that the PSA unit is replaced with the addition of MS and cryogenic separator (CRYS) units. By doing so, the system reliability in Scenario 4 is slightly higher compared to Scenario 3. In Scenario 4, the power generated from the system is only 14.11 MW. There is still a big gap compared to the desired power demand of 20 MW. Even though the power demand was not achieved, there is still a small fraction of EFB fuel that is not utilised. This is because by increasing the feed flow, it will increase the total capacity in the solid biomass process line. A slight increase in the feed flow would lead to the addition of a new type of technology. In this respect, it is not feasible to add on an additional technology for a slight increase of feed flow. Hence, a balance between the equipment cost and the amount of energy generated had to be determined.

Results from Scenario 4 showed the limitation of the energy generation due to the available amount and type of biomass in this case study. The highest power energy that can be generated with the available amount of biomass fuel in this case study is between 14 to 15 MW. By increasing the power demand beyond this limit would lead to a significant decrease in the trade-off degree of satisfaction. This is because the system is not able to achieve the power demand, hence the flexibility of the system decreases significantly.

Fig. 8. Scenario 4 optimal biomass CHP design

Table 8 presents the summary of the result for Scenarios 1-4. The changes of the degree of satisfactions for four different scenarios is plotted and shown in Fig. 9. In Scenario 1, λ^{FLEX} was fully maximised (more than 0.95) while, λ^{COST} and $\lambda^{RELIABILITY}$ were partially satisfied at 0.65. Results from Scenarios 1-3 showed a trade-off was achieved without completely neglecting other objectives.

Table 8. Result summary of Scenarios 1-4

Fig. 9. Degree of satisfaction comparison for four scenarios (a = Cost, b = Flexibility, c = Reliability, and d = Trade-off)

The λ of the system in Scenario 4 reduced significantly compared to Scenarios 1-3. This is because of the power requirement exceeding the maximum capacity limit of the CHP design. In this sense, the model returned an optimum result where all three objectives were partially satisfied. Fig. 9 showed that as the power demand increases, λ will starts to decrease. On the other hand, λ increased incrementally when the power demand increased from Scenarios 1-2. The power generation capability of the biomass CHP system in this case study is around 0-14 MW. The highest λ was achieved when the biomass CHP design under 10 MW power requirement.

4.5 Scenario 5 : Power Demand of 5 MW using Non-Linear Model

In Scenario 5, a mixed-integer non-linear programming (MINLP) model was developed to compare its performance with the linear model used in Scenarios 1-4. The difference between the two models is that the MINLP model utilised the conventional non-linear expression (shown in Eq. (21)) in optimising the system reliability instead of the linear approach proposed (Eqs. (22) – (24)). The MINLP model consists of total 527 variables, 43 integers, 56 non-linear variables, 535 constraints, and 15 non-linear constraints. This non-linear model was solved within 3 minutes.

In Scenario 5, the same data, information, and superstructure developed in Section 3 are used. The optimal design of a 5 MW power demand biomass CHP system was generated using the MINLP model. Fig. 10 presents the optimal CHP biomass design in Scenario 5. Compared to the design generated using the MILP model (Scenario 1), the number of technologies selected using the MINLP model is way lesser. This is because of the different in system reliability approach, instead of using a new variable relative reliability to represent the system reliability, MINLP formulates the system reliability as one of the objectives. Even though the reliability of the system generated through MINLP model is 0.98, but the solid biomass process line employed a series system arrangement. This would mean that failure of either drying or gasifier technology would cause the shutdown of the entire solid biomass process line. Such vulnerability may require a high frequency of unscheduled maintenance in this biomass CHP design. Concurrently, only PKS and PMF were selected for the solid biomass process. PKS and PMF were selected because of their high calorific value compared to other types of solid biomass feed. Because of PKS and PMF have a relatively small size (Refer to Table 2 in Section 3), a shredder is not required in the design of this system. Meanwhile, for the drying process only flash dryer (FD) technology was selected. This is because FD unit has the highest reliability compared to other types of dryers. Out of all the technologies options to convert solid biomass fuel to product, only FBG unit is selected. This is because compared to boilers, gasifiers have higher efficiency and among the gasifiers technologies considered, FBG has the highest reliability and conversion rate. Meanwhile, the configuration for the liquid biomass process is exactly the same as the one generated using MILP model, there are two different gas impurities separation technologies (i.e., PSA and MS) and three different energy generation technologies (i.e., GT2, GE2, and MT2). Because of the number of technologies is greatly reduced in the solid biomass process, the model increases the system reliability through the configuration of liquid biomass technologies. The cost of the system is greatly reduced compared to the application of MILP model (Scenario 1). This is because of the reduction in number of technologies. However, the drawback to this is that the system reliability is lower. Especially in the solid biomass production line. There is only one type of dryer and one type of gasifier is selected in the configuration. This also means that failure of either FD or FBG units would lead to the shutdown of the entire solid biomass operation. The system reliability remains high (0.98) because of the configuration in liquid biomass process.

The comparison of MILP model and MINLP model based on the results from Scenario 1 and 5 are presented in Table 9.

Fig. 10. Optimal biomass CHP design in Scenario 5

Table 9. Comparison of MILP (Scenario 1) and MINLP model (Scenario 5)

Results from Table 9 showed that the MINLP model has higher degrees of satisfaction compared to the MILP model, but it requires a longer time to solve the model. Even though the result of MINLP model shows better performance, but the resultant reliability computed using MINLP model for the solid biomass is considered low (with only one type of dryer and gasifier unit). Meanwhile, the result from MILP model showed that the system reliability for the solid biomass process is over maximised (three types of dryers and two types of boilers were selected). It is important to note that solutions from both the MILP and MINLP models are not “better” than one another. Based on the core principles behind multi-objective optimisation, multi-objective problems contain a set of optimal solutions rather than just a single “best” solution. This set of optimal solutions is otherwise known as the Pareto set. From the Pareto set, it is typical of the decision-maker to choose a suitable solution from based on preference. A solution is considered part of the Pareto set if no improvement is possible in one objective without losing in other objectives (Andiappan, 2017). This can clearly be seen when comparing the solutions obtained from Scenario 1 and Scenario 5. When compared to the solution in Scenario 5, the solution from Scenario 1 may be weaker in terms of cost but performs better in terms of system reliability and flexibility. This evident indicates that both solutions belong to a Pareto set of optimal solutions. Thus, it is up to the decision-maker to determine a suitable solution based on individual preference when designing the system. If cost can be sacrificed, the result from MILP model would be preferred. On the other hand, the result from MINLP model would be preferred if the decision maker is willing to compromise on both system reliability and to make additional contingencies available for unscheduled maintenances due to failure of equipment. This also means that both MILP and MINLP models can be used to assist in the decision making for the design of a biomass CHP system. This also justified that the MILP model can be used as an alternative to the normal MINLP model in assisting the synthesis of the optimal biomass CHP design.

4.6 Further Analysis of Technology Selection

By combining the result from all the scenarios presented (1 to 5), technologies that were frequently selected are identified. Based on the number of selections for each technology in five scenarios, the technologies can be classified into three classes: "Must have", "optional", and "must avoid". The "must-have" technologies are the ones that were selected in all five scenarios. The "optional" technologies are the ones that were selected at least once in all the five scenarios. Whereas the "must avoid" technologies are the ones that were not selected at all in all five scenarios. Table 10 presents the technologies under the three different classes.

Table 10. Classification of technologies based on the number of selections.

In the pre-treatment process, FD and DIG units were heavily favoured. FD unit has the highest reliability compared to other types of dryers. The operational cost of this type of dryer is also the lowest within the three types of dryers. SDD unit is the least favoured drying technology. This is because SSD unit has the lowest reliability and highest cost within the three different technologies. DIG unit is used to convert the liquid biomass fuel (i.e., POME) to biogas. As long as there is a supply of POME to the system, the DIG unit would be required. On the other hand, Shredder is only required if the solid biomass fuel is in larger size (> 10 cm). In Scenario 5, PKS and PMF which are smaller size (< 10 cm) of biomass fuel did not require shredding process. Both boilers and gasifiers technologies are generally favoured in the application to convert solid biomass into products (syngas or steam). SB, FBB, and FBG units are selected four times in the total five scenarios. This is because boilers and FBG units have high reliability (≥ 0.9). Steam turbines (HPST and MPST) and stirling engine, SE units are connected to boilers technologies. The selection of boilers units would equal to the selection of either steam turbines (HPST and MPST) or SE units. Among the energy generation technologies for syngas, only GE1 and MT1 units were selected in some of the scenarios. This is because GT1 unit is equipped with the heat recovery steam generator, HRSG1 unit. The selection of GT1 unit in the conversion of syngas to energy would require an additional unit HRSG1. Chemical scrubber (CS) is the least favoured gas impurities separation technology for biogas. Compared to other types of technologies, CS has the lowest reliability with only 0.57.

5. Conclusion and future recommendation

This work had presented a fuzzy optimisation model to synthesise an optimal design of a biomass CHP system considering total cost, flexibility, and reliability simultaneously. The model was developed using linear expressions for system reliability instead of the conventional non-linear expressions. A case study is conducted to illustrate the proposed approach. In the case study, the biomass fuels selected are the waste from palm oil and wood mills. Four scenarios with different power demands (5, 10, 15, and 20 MW) were solved in this case study. Following this, the proposed linear model was compared to a non-linear model that used the conventional non-linear expressions for system reliability. Results from the comparison showed that the proposed linear model can be used as an alternative to the non-linear model in assisting the decision making of synthesising an optimal biomass CHP design. Further analysis in the case study has also identified a list of essential, optional, and unnecessary types of technologies. Future work may consider alternative technologies and other renewable energy sources. Factors like emissions, availability and others can be incorporated as one of the objectives in synthesising the design. Biomass CHP is considered as an energy-efficient system. Thus, by taking into consideration the emissions in synthesising the design of the system, a great amount of emission could be further reduced. As an extension to the current biomass CHP system, the uncertainty or inconsistency of the biomass supply and properties may be considered. Biomass properties vary depending on the sources, and such changes would affect calorific value and the selection of the technologies and fuels. Another consideration for future work is the integration of surrogate models. Surrogate models closely mimic the behaviour of a technology using large statistical data. This is suitable to predict technology performances more accurately.

Compliance with Ethical Standards

Conflict of Interest - the authors declare that they have no conflicts of interest.

Acknowledgements

This author would like to acknowledge the support from the School of Engineering and Physical Sciences of Heriot-Watt University Malaysia. The technical support from LINDO SYSTEMS INC. for providing the LINGO v18.0 software is gratefully acknowledged too.

References

Ahmed, A., Esmaeil, K. K., Irfan, M. A., & Al-Mufadi, F. A. (2018). Design methodology of heat recovery steam generator in electric utility for waste heat recovery. *International Journal of Low-Carbon Technologies*, *13*(4), 369–379.

Akrami, A., Doostizadeh, M., & Aminifar, F. (2019). Power system flexibility: an overview of emergence to evolution. *Journal of Modern Power Systems and Clean Energy*, *7*(5), 987–1007.

Alizadeh, M. I., Parsa Moghaddam, M., Amjady, N., Siano, P., & Sheikh-El-Eslami, M. K. (2016). Flexibility in future power systems with high renewable penetration: A review. *Renewable and Sustainable Energy Reviews*, *57*, 1186–1193.

Amrutkar, K. P., & Kamalja, K. K. (2017). An overview of various importance measures of reliability system. *International Journal of Mathematical, Engineering and Management Sciences*, *2*(3), 150–171.

Andiappan, V. (2017). State-Of-The-Art Review of Mathematical Optimisation Approaches for Synthesis of Energy Systems. *Process Integration and Optimization for Sustainability*, *1*(3), 165–188.

Andiappan, V., Benjamin, M. F. D., Tan, R. R., & Ng, D. K. S. (2019). Design, optimisation and reliability allocation for energy systems based on equipment function and operating capacity. *Heliyon*, *5*(10), e02594.

Andiappan, V., Ng, D.S., Tan, R.R. (2017) Design operability and retrofit analysis (DORA) framework for energy systems. *Energy* 134, 1038–1052.

Andiappan, Viknesh & Benjamin, Michael Francis & Tan, Raymond & Ng, Denny K S. (2018). An Integrated Framework to Address Criticality in Biomass Tri-Generation Systems via Redundancy Allocation. *Process Integration and Optimization for Sustainability*.

Arsham, Dr. Hossein (2014) Deterministic Modeling: Linear Optimization with Applications.

Atadious, D., & Joel, O. (2017). Design and Construction of a Plastic Shredder Machine for Recycling and Management of Plastic Wastes. *Journal of Multidisciplinary Engineering Science and Technology (JMEST)*, *4*(9), 2458–9403. Retrieved from www.jmest.org

Benjamin, Michael Francis & Andiappan, Viknesh & Lee, Jui-Yuan & Tan, Raymond. (2020). Increasing the reliability of bioenergy parks utilizing agricultural waste feedstock under demand uncertainty. *Journal of Cleaner Production*. 269. 122385.

Bhosale, K. C., & Pawar, P. J. (2018). Material Flow Optimisation of Flexible Manufacturing System using Real Coded Genetic Algorithm (RCGA). *Materials Today: Proceedings*, *5*(2), 7160–7167.

BP. (2019). BP Statistical Review of World Energy Statistical Review of World. *The Editor BP Statistical Review of World Energy*, 1–69.

Brandin, J., Tunér, M., Odenbrand, I., & Lund, V. (2011). *Small Scale Gasification : Gas Engine CHP for Biofuels*.

Carlini, M., Mosconi, E. M., Castellucci, S., Villarini, M., & Colantoni, A. (2017). An economical evaluation of anaerobic digestion plants fed with organic agro-industrial waste. *Energies*, *10*(8), 1–15.

Chong, Fah Keen & Andiappan, Viknesh & Ng, Denny K S & Foo, Dominic & Eljak, Fadwa & Atilhan, Mert & Chemmangattuvalappil, Nishanth. (2017). Design of Ionic Liquid as Carbon Capture Solvent for a Bioenergy System: Integration of Bioenergy and Carbon Capture Systems. *ACS Sustainable Chemistry & Engineering*, *5(6)*, 5241-5252.

Crippa, M., Oreggioni, G., Guizzardi, S., Muntean, M., Schaaf, E., Lo Vullo, E., … Vignati, E. (2019). Fossil CO2 and GHG emissions of all world countries. In *European Comission*.

Cui, Y., Geng, Z., Zhu, Q., & Han, Y. (2017). Review: Multi-objective optimization methods and application in energy saving. *Energy*, *125*, 681–704.

De Rosa, M., Carragher, M., & Finn, D. P. (2018). Flexibility assessment of a combined heat-power system (CHP) with energy storage under real-time energy price market framework. *Thermal Science and Engineering Progress*, *8*(October 2018), 426–438.

Ebeling, C., 1997. An Introduction to Reliability and Maintainability Engineering. McGraw-Hill, New York.

Ebrahimi, M., & Keshavarz, A. (2015a). CCHP Evaluation Criteria. *Combined Cooling, Heating and Power*, 93–102.

Ebrahimi, M., & Keshavarz, A. (2015b). CCHP Technology. *Combined Cooling, Heating and Power*, 35–91.

Ekwonu, M. C., Perry, S., & Oyedoh, E. A. (2013). Modelling and simulation of gas engines using aspen HYSYS. *Journal of Engineering Science and Technology Review*, *6*(3), 1–4.

Elsido, C., Bischi, A., Silva, P., & Martelli, E. (2017). Two-stage MINLP algorithm for the optimal synthesis and design of networks of CHP units. *Energy*, *121*, 403–426.

EPRI Technical Report (2002). Stirling Engine Assessment, EPRI, Palo Alto, 1007317.

Ferreira, A. C., Oliveira, R. F., Nunes, M. L., Martins, L. B., & Teixeira, S. F. (2014). Modelling and Cost Estimation of Stirling Engine for CHP Applications. *International Conference on Mechanics, Fluid Mechanics, Heat and Mass Transfer*, *Power Syst*, 21–29.

Foong, S., Andiappan, V., Tan, R., Foo, D., Ng, D. (2019). Hybrid Approach for Optimisation and Analysis of Palm Oil Mill. *Processes 7(2)*, 100.

Foong, S.Z.Y., Lam, Y.L., Andiappan, V., Foo, D.C.Y., Ng, D.K.S. (2018). A Systematic Approach for the Synthesis and

Optimization of Palm Oil Milling Processes. Ind. Eng. Chem. Res. 57, 2945–2955.

Gunantara, N. (2018). A review of multi-objective optimization: Methods and its applications. *Cogent Engineering*, *5*(1), 1–16.

Haghifam, M. R., & Manbachi, M. (2011). Reliability and availability modelling of combined heat and power (CHP) systems. *International Journal of Electrical Power and Energy Systems*, *33*(3), 385–393.

Haque, N., & Somerville, M. (2013). Techno-economic and environmental evaluation of biomass dryer. *Procedia Engineering*, *56*, 650–655.

International Renewable Energy Agency (2012). Biomass for Power Generation (Vol. 119).

Jain, A. K. (2007). A Review of Fixed Bed Gasification Systems for Biomass. *E-Journal - Internationale Kommission Für Agrartechnik*, *9*(January).

Karakurt, A. S., & Güneş, Ü. (2017). Performance analysis of a steam turbine power plant at part load conditions. *Journal of Thermal Engineering*, *3*(2), 1121–1128.

Korte, R. F. (2003). Biases in Decision Making and Implications for Human Resource Development. *Advances in Developing Human Resources*, *5*(4), 440–457.

Koruba, D., Piotrowski, J. Z., & Latosińska, J. (2017). Biomass - Alternative renewable energy source to the fossil fuels. *E3S Web of Conferences*, *14*(March 2016), 1–10.

Lannoye, E., Flynn, D., O'Malley, M. (2012). Evaluation of power system flexibility. IEEE Trans. Power Syst. 27, 922–931.

Ling, W. C., Andiappan, V., & Kin Wan, Y. (2018). Design of Biomass Combined Heat and Power (CHP) Systems based on Economic Risk using Minimax Regret Criterion. *MATEC Web of Conferences*, *152*, 1–16.

Loh, S. K., Nasrin, A. B., Mohamad Azri, S., Nurul Adela, B., Muzzammil, N., Daryl Jay, T., … Kaltschmitt, M. (2017). First Report on Malaysia's experiences and development in biogas capture and utilization from palm oil mill effluent under the Economic Transformation Programme: Current and future perspectives. *Renewable and Sustainable Energy Reviews*, *74*(February), 1257–1274.

Lok, W.J., Ng, L.Y., Andiappan, V. (2020). Optimal decision-making for combined heat and power operations: A fuzzy optimisation approach considering system flexibility, environmental emissions, start-up and shutdown costs. Process Saf. Environ. Prot. 137, 312–327.

Martins, F., Felgueiras, C., Smitkova, M., & Caetano, N. (2019). Analysis of fossil fuel energy consumption and environmental impacts in european countries. *Energies*, *12*(6), 1–11.

Mermoud, F., Haroutunian, A., Faessler, J., & Lachal, B. (2015). Impact of load variations on wood boiler efficiency and emissions. *Archives Des Sciences*, *41*(0), 27–38.

Mohammad, M. A. T. A., Ahmed, M. M. A., & Mohammad, O. A. F. (2017). *Effect of Load Variation on Steam Unit*.

Naimi, L. J., Sokhansanj, S., Mani, S., Hoque, M., Bi, T., Womac, A. R., & Narayan, S. (2006). The Canadian Society for Bioengineering Cost and Performance of Woody Biomass Size Reduction for Energy Production. *CSBE/SCGAB 2006 Annual Conference*.

Ng, D. K. S., Tan, R. R., Foo, D. C. Y., & El-halwagi, M. M. (2016). *Process Design Strategies for Biomass Conversion Systems*.

Nuytten, T., Claessens, B., Paredis, K., Van Bael, J., & Six, D. (2013). Flexibility of a combined heat and power system with thermal energy storage for district heating. *Applied Energy*, *104*, 583–591.

Olivier, J. G. J., & Peters, J. A. H. W. (2020). Trends in Global CO2 and Total Greenhouse Gas Emissions: Report 2019. *PBL Netherlands Environmental Assessment Agency*, *2020*(February), 70.

Paganin, L., & Borsato, M. (2017). A Critical Review of Design for Reliability - A Bibliometric Analysis and Identification of Research Opportunities. *Procedia Manufacturing*, *11*(June), 1421–1428.

Perea-Moreno, M. A., Samerón-Manzano, E., & Perea-Moreno, A. J. (2019). Biomass as renewable energy: Worldwide research trends. *Sustainability (Switzerland)*, *11*(3).

Pérez-Uresti, S. I., Martín, M., & Jiménez-Gutiérrez, A. (2019). Superstructure approach for the design of renewable-based utility plants. *Computers and Chemical Engineering*, *123*, 371–388.

Pérez-Uresti, S. I., Martín, M., & Jiménez-Gutiérrez, A. (2020). A Methodology for the Design of Flexible Renewable-Based Utility Plants. *ACS Sustainable Chemistry and Engineering*.

Rahayu, A. S., Karsiwulan, D., Yuwono, H., Trisnawati, I., Mulyasari, S., Raharjo, S., … Paramita, V. (2015). Handbook POME-to-Biogas Project Development in Indonesia. *Winrock International*, 98.

Ruiz-Rodriguez, F. J., Gomez-Gonzalez, M., & Jurado, F. (2014). Reliability optimization of an electric power system by biomass fuelled gas engine. *International Journal of Electrical Power and Energy Systems*, *61*, 81–89.

Sacaan, R., Rudnick, H., Lagos, T., Ordonez, F., Navarro-Espinosa, A., & Moreno, R. (2017). Improving power system reliability through optimization via simulation. *2017 IEEE Manchester PowerTech, Powertech 2017*, (June).

Sarbu, I., & Sebarchievici, C. (2016). Vapour Compression-Based Heat Pump Systems. *Ground-Source Heat Pumps*, 7–25.

Schmidt, M., Schöbel, A., & Thom, L. (2019). Min-ordering and max-ordering scalarization methods for multi-objective robust optimization. *European Journal of Operational Research*, *275*(2), 446–459.

Silva, A. & Brito, Jorge & Gaspar, Pedro. (2016). Methodologies for Service Life Prediction of Buildings.

Song, B., Hutabarat, W., Tiwari, A., & Enticott, S. (2016). Integrating optimisation with simulation for flexible manufacturing system. *Advances in Transdisciplinary Engineering*, *3*(December 2018), 175–180.

Swaney, R.E., Grossmann, I.E. (1985). An index for operational flexibility in chemicalprocess design. Part 1: formulation and theory. AIChE J. 31, 621–641.

U.S. Environmental Protection Agency. (2007). Biomass Combined Heat and Power Catalog of Technologies. *Biomass*, (September), 2000–2003.

U.S. Environmental Protection Agency. (2015). *Catalog of CHP Technologies*.

Wang, H., Zhang, H., Gu, C., & Li, F. (2017). Optimal design and operation of CHPs and energy hub with multi objectives for a local energy system. *Energy Procedia*, *142*, 1615–1621.

Yang, L., Niu, R., Xie, J., Qian, B., Song, B., Rong, Q., & Bernstein, J. (2011). Design-for-reliability implementation in microelectronics packaging development. *Microelectronics International*, *28*(1), 29–40.

Zhang, D., Evangelisti, S., Lettieri, P., & Papageorgiou, L. G. (2015). Optimal design of CHP-based microgrids: Multiobjective optimisation and life cycle assessment. *Energy*, *85*, 181–193.

Zhao, Y., Chen, H., Waters, M., & Mavris, D. N. (2003). Modeling and cost optimization of combined cycle heat recovery generator systems. *American Society of Mechanical Engineers, International Gas Turbine Institute, Turbo Expo (Publication) IGTI*, *1*, 881–891.

Zimmermann, H.-J. (1978). Fuzzy programming and linear programming with severalobjective functions. Fuzzy Sets Syst. 1, 45–55.

Zimmermann, H.-J. (1983). Fuzzy mathematical programming. Computers & operations. Research 10, 291–298.