



Supply chain optimisation of pyrolysis plant deployment using goal programming



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ABSTRACT

This paper presents a goal programming model to optimise the deployment of pyrolysis plants in Punjab, India. Punjab has an abundance of waste straw and pyrolysis can convert this waste into alternative bio-fuels, which will facilitate the provision of valuable energy services and reduce open field burning. A goal programming model is outlined and demonstrated in two case study applications: small scale operations in villages and large scale deployment across Punjab's districts. To design the supply chain, optimal decisions for location, size and number of plants, downstream energy applications and feedstocks processed are simultaneously made based on stakeholder requirements for capital cost, payback period and production cost of bio-oil and electricity. The model comprises quantitative data obtained from primary research and qualitative data gathered from farmers and potential investors. The Punjab district of Fatehgarh Sahib is found to be the ideal location to initially utilise pyrolysis technology. We conclude that goal programming is an improved method over more conventional methods used in the literature for project planning in the field of bio-energy. The model and findings developed from this study will be particularly valuable to investors, plant developers and municipalities interested in waste to energy in India and elsewhere.

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1. Introduction

The Indian state of Punjab, like the rest of India, has seen a rapid growth in demand for energy and waste management services. Unlike other Indian states, Punjab does not have access to hydro-electric, coal, or similar resources, and thus relies heavily on imports of energy from other states. However, Punjab does have an abundance of agricultural waste biomass, particularly rice and wheat straw. Singh et al. [1,2] determined the spatial availability of unused agricultural biomass in Punjab using a Geographical Information System (GIS). They found that 14 mega tonnes of waste biomass was produced every year; the majority of which was waste straw (3 mega tonnes of wheat straw, 7 mega tonnes of rice straw).

Energy conversion of waste biomass is not widely practiced in Punjab or the other states of India, and the majority of waste straw is disposed of through open field burning. This has severe environmental and social impacts, including greenhouse gas,

carcinogenic and particulate matter emissions. The carbon dioxide and carbon monoxide emissions from wheat straw burnt with a low combustion efficiency range from 1400 to 1600 g CO₂/kg and 35–60 g CO/kg [3–5]. As a result of straw being burnt, fields lose nutrients and carbon, thus additional fertiliser, pesticides and irrigation are required [6]. Particulate matter is a major nuisance, causing a range of health problems: allergies, asthma, eye irritation, bronchial problems and other respiratory issues. It has been reported that the average household in Punjab has to spend more than Rs.1000 (\$18.5) per year to address these medical conditions. It has been estimated that the total cost incurred as a result of pollution from straw burning in Punjab is as high as Rs.76 million/year (\$1,270,000) [7]. Thus there is an urgent requirement for innovative solutions to provide energy services and alleviate the problems from open field burning in Punjab.

Straws and cereal crops are particularly difficult to process via controlled combustion methods. Due to a high alkali, silicon, chlorine and sulphur content, they are highly fouling and slagging. Rice straw for example has an ash content of around 15% comprising of approximately 75% silicon and 10% potassium. Combustion of rice straw also results in high levels of oxides of

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Nomenclature	
ARice	availability of rice straw (ktpa)
AWheat	availability of wheat straw (ktpa)
Bo	percentage of bio-oil blended with diesel (%)
Ca	cost of accessories (million\$)
Capex	capital cost (million\$)
cd	cost of diesel (\$/l)
Ce	cost of diesel engine (million\$)
CO2R	prevented carbon dioxide emissions (tpa)
Cp	cost of pelletiser (million\$)
Cpyro	cost of pyrolysis unit (million\$)
CRice	cost of rice straw (\$/kg)
cw	wage of tractor driver (\$/h)
CWheat	cost of wheat straw (\$/kg)
DRice	demanding rice straw (ktpa)
ds	average distance of feedstock from plant (km)
DWheat	demanding wheat straw (ktpa)
Ec	engine capacity (kW)
Efc	engine fuel consumption (kg/h/kW)
fc	fuel consumption of tractor (l/km)
FCR	fixed charge rate (%)
Income	plant income (million\$/year)
kd	discount rate (%)
LCOE	levelised cost of electricity (\$/kWh)
LCOO	levelised cost of bio-oil (Rs./kg)
lt	capacity of tractor trolley (tonnes)
n	period of loan (years)
NP	number of plants (–)
O&M _{total}	total operations and maintenance costs (million\$/year)
Oe	annual operating cost of engine (million\$/year)
Of	annual purchasing cost of feedstock (million\$/year)
Op	annual operational cost of pelletiser (million\$/year)
Opyro	annual operational cost of pyrolysis unit (million\$/year)
Ot	annual operational cost of transporting feedstock (million\$/year)
Ow	annual operation cost of storing feedstock in a warehouse (million\$/year)
P	profit of plant (million\$/year)
Pc	plant capacity (kg/h)
Pl	plant's parasitic load (kW)
PLCapex	percentage of capital cost paid for by loans (%)
PMR	prevented particulate matter emissions (tpa)
PP	payback period (years)
Qc	quantity of char produced (tpa)
Qe	quantity of electricity produced (kWh/year)
Qo	quantity of bio-oil produced (tpa)
QSe	quantity of surplus electricity after parasitic requirements (kWh/year)
QSo	quantity of surplus bio-oil after parasitic requirements (tpa)
Sc	sale price of char (\$/kg)
Se	sale price of electricity (\$/kWh)
So	sale price of bio-oil (\$/kg)
ta	total area of target location (km ²)
ts	tractor speed (km/h)
Yc	yield of bio-char (%)
Yo	yield of bio-oil (%)
<i>Sub- super- script</i>	
+d	positive deviation from goal
–d	negative deviation from goal
l	variable site locations
w	weighting of goal deviation

nitrogen and sulphur being emitted. Special solution are therefore required to process rice straw and other waste crop residues for the purposes of energy generation [8].

Pyrolysis is a thermochemical conversation process that converts organic materials at high temperatures in the absence of oxygen to produce alternative bio-fuels: bio-oil, bio-char and pyrolysis gas [9]. Resulting bio-oil has low alkali metal content and can be used as an alternative fuel by blending with conventional liquid fuels [10]. Fermentation and hydrocracking enable transportation fuels to be produced and other chemical feedstocks such as phenols and organic acids can be extracted. Pyrolysis gas is useful as it contains methane and hydrogen, though its calorific value is much lower than that of convention fuels due to the substantial fraction of nitrogen and carbon dioxide present. Bio-char is the remaining solid residue and acts as a carbon sequestration material and can be used for soil amendment and water treatment [11–13]. Though pyrolysis has started to gather much interest in the field of waste to energy, as there is significant revenue potential in these alternative products, to the authors' knowledge, no installed facilities exist in India and research into these types of systems remains limited [14]. There are many options for deploying pyrolysis plants in India and the alternative upstream and downstream activities for generating bio-fuels from residue straws are numerous and complex. The main supply chain and logistic issues for producing energy from biomass are reviewed by Gold and Seuring [15]. The five main system components of the extended supply chains for biomass utilisation are harvesting and collection, preparation/pre-treatment, storage, transport and energy conversion.

1.1. Multi-criteria decision-making

Multi-Criteria Decision-Making (MCDM) methods enable a systematic and holistic approach to be taken to strategic decision-making and supply chain design. Thus, the uptake of MCDM for renewable energy planning has increased significantly in recent years. Pohekar and Ramachandran [16] provided a review of MCDM techniques and studies that have been performed for sustainable energy planning and Scott et al. [17] reviewed MCDM methods for bio-energy systems. In the field of bio-energy, several authors have used MCDM to optimise biomass supply chains focussing on specific aspects of the logistical operations; applications include resource allocation, site selection, vehicle scheduling and technology selection [18,19]. Miet Van Dael et al. [20] outlined an MCDM tool for determining potential sites for bio-energy projects in Belgium. Cornelissen et al. [21] used MCDM to rank different biopolymer options for blending with biomass for flash pyrolysis. Iakovou et al. [22] reviewed research that has been carried for strategic, tactical and operational decision-making in the five main areas of the biomass to energy supply chain and concluded that more work is required to evaluate the entire supply chain, rather than decision-making at a single stage of the supply chain.

Mixed integer programming is one of the most widely utilised MCDM tools for biomass supply chain optimisation. The approach involves optimising a range of decision variables in order to minimise or maximise a particular objective function. Frombo et al. [23] developed a tool that uses Mixed Integer Linear Programming (MILP) and GIS for evaluating alternative scenarios for forest

biomass utilisation. Decision variables included conversion processes, plant capacity and quantity of harvested biomass. The objective of the model was to maximise the net profit. Nagel [24] used MILP for evaluating alternative energy supplies from biomass based on demand and distribution requirements. Yu et al. [25] used a Mixed Integer Non Linear Programming (MINLP) model for maximising net present value and minimising environmental impact for the biomass to energy supply chain. Dunnett et al. [26] used a MILP model to determine optimal harvest dates, supply chain structure, storage strategy and operational and logistical scheduling with respect to minimising the total system cost for biomass to heat. Freppaz et al. [27] utilised a MILP-GIS model to optimise the exploitation of forest biomass for heat and power. The model was designed to aid decision makers on energy conversion plant sizing, heat to power ratio, and biomass collection quantities and location. The objective function minimised was based on sales, transportation costs, harvesting costs and operations and maintenance costs. Dyken et al. [28] utilised MILP to optimise the energy distribution of gas, electricity and heat from biomass facilities. Akgul et al. [29] applied MILP to investigate the supply chain for bio-fuels in the UK. Their model determined optimal values for biomass cultivation rates and sites, location and scale of bio-fuel facilities, biomass imports and modes of transport.

Applications of mixed integer programming are particularly prevalent in the literature for managing the supply chain of bio-refineries. Ekşioğlu et al. [30] used a mixed integer program to evaluate the logistical issues for supplying biomass to a bio-refinery. They applied their model to two case studies for corn stover and woody biomass to C-ethanol in Mississippi and decisions were recommended for plant number, size and location. Huang et al. [31] outlined a MILP model to determine the minimum cost for supplying ethanol from different biomass wastes. Decision variables included the type of feedstock, capacity of refinery and plant opening times. Evaluated feedstocks included wheat straw, municipal solid waste, corn stover, forest residues and rice straw. Akgul et al. [32] also applied an MILP model for cost minimisation of the bio-ethanol supply chain in Northern Italy. Marvin et al. [33] presented a MILP model for optimising the net present value for a lignocellulosic biomass to ethanol conversion supply chain. Additional studies of a similar nature are reviewed in more detail by Srivastava in Ref. [34].

Goal programming is another widely adopted MCDM tool; however, applications for bio-energy planning and management are relatively limited. Kanniappan and Ramachandran [35] used goal programming for planning electricity production from biomass in India. Goal programming has also been used for natural resource management in Mozambique [36], optimising land utilisation for bio-energy crops [37] and bio-energy supply chain design in Ontario [38]. Goal programming builds on linear programming models to enable multiple and often conflicting objectives to be evaluated and optimised. This is achieved by allowing goals/targets to be specified and optimal tradeoffs among decision variables to be made in order to minimise deviations from these goals.

The reviewed literature identifies that there is a need for decision-making methods that can consider the entire supply chain. In particular, there is a lack of research on optimising the deployment of specific bio-energy conversion technologies. The aim of this study is to outline and demonstrate the application of a method to specify the optimal decisions for deploying pyrolysis plants in Punjab to alleviate field burning and provide valuable energy services and fuels to the area. Specifically, a detailed plan for deploying pyrolysis plants in Punjab will be established by utilising the benefits of a Mixed Integer Non Linear Goal Programming Model (MINLGP). While combining goal programming with mixed

integer non linear programming increases complexity, it will enable stakeholder specified targets to be achieved and stakeholder requirements to be incorporated into the decision rationale for supply chain design. The intention is that this will ultimately promote the uptake of pyrolysis and other energy conversion technologies for generating bio-fuels (bio-oil and char) from unused waste straw in India and elsewhere.

The methodology adopted to achieve this aim is outlined in the following section. In Section 3 the pyrolysis technology considered in this study and its supply chain is described. The goal programming model is outlined in Section 4, and Section 5 details its application to two alternative case studies. The results of the case studies are provided and evaluated in Section 6. The paper concludes by discussing the implications of the developed model and its wider applications.

2. Methodology

A model is developed to optimise the supply chain for pyrolysis plant deployment in Punjab, India. The model is based on a mixed integer non linear goal programming approach that enables optimal decisions for the design of the supply chain to be made based on specified goals (targets) and weightings attributed to deviations from these goals. In this study, these goals are stakeholder requirements for capital cost, feedstock utilisation, payback period and production costs for bio-oil and electricity. The optimal decisions to achieve these goals are made for plant location, size, number, outputs and type of feedstock utilised.

The model is demonstrated using case studies based on qualitative and quantitative data that has been gathered using both primary and secondary research methods. Quantitative data has been collected from the literature and a prototype pyrolysis plant operating in the Rupnagar district, Punjab. Qualitative data for the model goals and importance of deviations from these goals has been gathered from two alternative stakeholder groups: farmers and investors. By carrying out workshops, surveys and interviews we have determined what the stakeholder requirements are and established an importance to any deviations from their target requirements.

Two case studies are investigated for deploying pyrolysis systems in Punjab: small scale deployment in villages and large scale implementation across the districts of Punjab. Site specific data has been collected from several candidate locations that have an abundance of waste straw. This includes three rural villages in Rupnagar and five Punjab districts. Due to varying stakeholder opinions, results are generated for the different locations from both the farmers' and investors' perspectives.

3. The pyrolysis plant

The performance and cost characteristics of the pyrolysis technology considered in this study are based on the preliminary finding from system prototypes that have been developed by the European Bioenergy Research Institute (EBRI), Aston University, UK [39]. Pilot plants have been implemented in both the UK and India [40] and further details on the system can be found in Ref. [9]. The technology can be sized to process 10–100 kg/h of waste straw at 300–550 °C. The resulting bio-fuel products produced, as a percentage of the waste input, are approximately 35% bio-oil, 35% bio-char and 30% non-condensable gas. The plant has an auxiliary parasitic load requirement ranging from 5 to 25 kW, depending on the pyrolysis unit's capacity, so a proportion of the bio-oil is used to power the plant. In order to use bio-oil in a stationary diesel engine, it is blended with diesel. Depending on the quality of the bio-oil, a suitable blend is used in order to maintain a high fuel quality. The

diesel engine operates on a 30% blend of bio-oil from wheat straw (70% diesel) and 20% bio-oil blend when using rice straw (80% diesel). The engine fuel consumption is approximately 0.28 kg/kWh when using bio-oil from wheat straw and 0.3 kg/kWh whilst operating with bio-oil produced from rice straw. The supply chain from suppliers to customers for a pyrolysis plant operating in Punjab is shown in Fig. 1.

4. Goal programming model

The purpose of the goal programming model is to optimise the supply chain based on user specified goals/targets. The overall objective function of the model is to try and minimise any deviations from specified goals (unless desirable). These goals relate to conflicting objectives for a pyrolysis system operating in Punjab. In order to try and achieve these goals, optimal decisions among all the possible decision variables are made. The model also consists of a range of system constraints and financial assumptions. The 2013 exchange rate of 1 Indian National Rupee (INR) to 0.0185 US Dollars has been used throughout the study.

4.1. Objective function

The objectives for the goal programming model have been determined through interactions with pyrolysis plant operators, investors and farmers; they are summarised as:

- To minimise the payback period and capital cost of the system
- To reduce the environmental and social impacts of field burning
- To produce low cost bio-fuels and electricity

The goal programming objective function is subsequently defined by considering positive and negative deviations, $^{+d}$ and $^{-d}$ respectively, from specified goals for the payback period, PP, capital cost, Capex, levelised cost of bio-oil, LCOO, and levelised cost of electricity, LCOE. To consider the objective of reducing the environmental and social impacts from open field burning, negative deviation from the available wheat and rice straw (AWheat and ARice) is to be minimised. Positive deviations from the available wheat and rice straw is not possible, thus the variables $AWheat^{+d}$ and $ARice^{+d}$ are eliminated. Weightings, w , are applied to differentiate the importance of the goal deviations. In order for the weightings to be comparable they are associated with a single percentage deviation from the target goal. Different location data, l , is used to account for the variability of data among different site locations.

$$\begin{aligned}
 \text{Minimise : } & \sum_{i=1}^n AWheat_w^{-d} \cdot \left(\frac{AWheat_l^{-d}}{AWheat_l \cdot 0.01} \right) \\
 & + ARice_w^{-d} \cdot \left(\frac{ARice_l^{-d}}{ARice_l \cdot 0.01} \right) + PP_w^{+d} \left(\frac{PP_l^{+d}}{PP \cdot 0.01} \right) \\
 & + PP_w^{-d} \left(\frac{PP_l^{-d}}{PP \cdot 0.01} \right) + Capex_w^{+d} \left(\frac{Capex_l^{+d}}{Capex \cdot 0.01} \right) \\
 & + Capex_w^{-d} \left(\frac{Capex_l^{-d}}{Capex \cdot 0.01} \right) + LCOO_w^{+d} \left(\frac{LCOO_l^{+d}}{LCOO \cdot 0.01} \right) \\
 & + LCOO_w^{-d} \left(\frac{LCOO_l^{-d}}{LCOO \cdot 0.01} \right) + LCOE_w^{+d} \left(\frac{LCOE_l^{+d}}{LCOE \cdot 0.01} \right) \\
 & + LCOE_w^{-d} \left(\frac{LCOE_l^{-d}}{LCOE \cdot 0.01} \right), \quad l = 1, 2, \dots, n
 \end{aligned} \tag{1}$$

4.2. Decision variables

The objective function is minimised by optimising the decision variables for deploying a pyrolysis plant, these variables include:

- Location of plant
- Type and quantity of feedstock utilised
- Size of pyrolysis unit
- Size of coupled diesel engine
- Number of plants

The demanded wheat and rice straw, DWheat and DRice, has to be less than the available straw.

$$DWheat_l \leq AWheat_l, \quad l = 1, 2, \dots, n \tag{2}$$

$$DRice_l \leq ARice_l, \quad l = 1, 2, \dots, n \tag{3}$$

The processing capacity of a pyrolysis plant, P_c , is typically limited to a range of 10–100 kg of feedstock per hour. However, this will vary depending on the pyrolysis reactor's design.

$$Pc_l \leq 100, \quad l = 1, 2, \dots, n \tag{4}$$

$$Pc_l \geq 10, \quad l = 1, 2, \dots, n \tag{5}$$

The engine capacity, E_c , has to be greater than the plant's parasitic load, thus,

$$Ec_l \geq Pl_l, \quad l = 1, 2, \dots, n \tag{6}$$

The number of plants, NP, is simply defined as,

$$NP_l \geq 0, \quad l = 1, 2, \dots, n \tag{7}$$

4.3. Systems constraints

The model is further characterised by several constraints:

- Costs of the pelletiser, pyrolysis unit, diesel engine, plant accessories, diesel, feedstock, transport and storage
- Operations and maintenance costs of the pelletiser, pyrolysis unit and diesel engine
- Quantities and production costs of bio-fuels and electricity
- Carbon dioxide and particulate matter emissions
- Key financial indicators (payback period, income, profits, etc.)

The capital cost of the plant is defined by summing the costs for the pyrolysis unit, C_{pyro} , diesel engine, C_e , pelletiser, C_p , and other accessories (heaters, motors, control unit and other smaller components), C_a . A capital subsidy, C_s , maybe considered depending on the availability of incentive schemes for a target location.

$$\begin{aligned}
 Capex + Capex_l^{+d} - Capex_l^{-d} = & (C_{pyro_l} + C_e_l + C_p_l + C_a_l) * (1 - C_s), \\
 & l = 1, 2, \dots, n
 \end{aligned} \tag{8}$$

The total operations and maintenance cost for the system, $O\&M_{total}$, is calculated from the maintenance costs of the pelletiser, pyrolysis unit and engine, Op , O_{pyro} and O_e . Other operating costs include the cost of feedstock, Of , transport, O_t , and storage, O_w . A fixed charge rate, FCR, of repayment on a percentage loan of the capital investment, $PlCapex$, is also modelled.

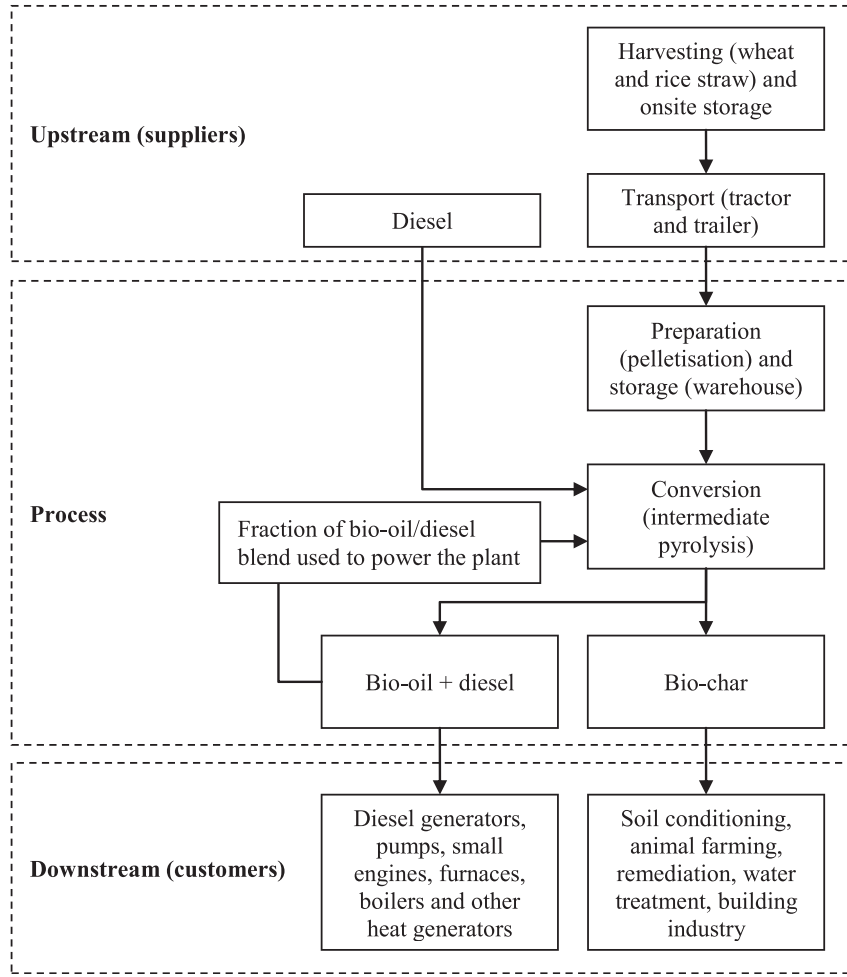


Fig. 1. Supply chain of a pyrolysis plant processing waste residue straws.

$$O\&M_{total} = \left[FCR \cdot PL_{Capex} \cdot (Capex + Capex_l^{+d} - Capex_l^{-d}) \right] + Op_l + Opyro_l + Oe_l + Ow_l + Ot_l + Of_l, \quad l = 1, 2, \dots, n \quad (9)$$

If loan repayments are required over an n number of years, a fixed charge rate is determined from the real or nominal discount rate, k_d . When variable annual operating costs or energy outputs need to be modelled, an alternative method for calculating the levelised cost of electricity should be used. The reader is referred to Ref. [41] for further details.

$$FCR = \frac{k_d(1 + k_d)^n}{(1 + k_d)^n - 1} \quad (10)$$

The total cost of feedstock depends on the quantities of wheat and rice straw demanded and their respective costs, $CWheat$ and $CRice$.

$$Of_l = CWheat_l \cdot DWheat_l + CRice_l \cdot DRice_l, \quad l = 1, 2, \dots, n \quad (11)$$

The total cost of transportation is a product of the feedstock's average distance from the plant, ds , total demanded raw material ($DWheat$ and $DRice$), cost of diesel, cd , vehicle fuel consumption, fc , wage cost for a transport labourer, cw , and transport speed, ts , which is all dependent on the load being transported, tl and number of plants, NP .

$$Ot = \frac{ds_l \cdot (DWheat_l + DRice_l) \cdot (cd \cdot fc + cw \cdot ts^{-1})}{tl \cdot NP_l \cdot 1000}, \quad l = 1, 2, \dots, n \quad (12)$$

The average distance to transport the fuel is based on the total area of the location, ta , and the assumption is made that the area is circular.

$$ds_l = \frac{2\sqrt{ta_l/\pi}}{3}, \quad l = 1, 2, \dots, n \quad (13)$$

The yields of bio-oil, Yo , and bio-char, Yc , can be influenced by a pyrolysis reactor's temperature and are stated as a percentage of the input feedstock's mass. The overall quantity of oil, Qo , and char, Qc , produced is then dependent on the number of plants, NP , and the plants' availabilities, Pa , and capacities, Pc . The quantity of surplus oil, QSo , to be sold, depends on the fuel consumption of the diesel generator, Efc , and the fuel mix ratio of bio-oil and diesel, Bo . Depending on the feedstock being processed, different blends with diesel will be useable in a stationary engine.

$$Qo_l = (Pa \cdot Yo \cdot NP_l \cdot Pc_l) / 1000, \quad l = 1, 2, \dots, n \quad (14)$$

$$Qc_l = (Pa \cdot Yc \cdot NP_l \cdot Pc_l) / 1000, \quad l = 1, 2, \dots, n \quad (15)$$

$$QSo_l = Qo_l - [Efc_l \cdot Pa \cdot Bo_l], \quad l = 1, 2, \dots, n \quad (16)$$

$$QSo_l \geq 0, \quad l = 1, 2, \dots, n \quad (17)$$

The quantity of electricity produced, Q_e , and the surplus electricity, Q_{Se} , remaining after powering the plant is found from,

$$Qe_l = \frac{Pa \cdot NP_l \cdot Ec_l}{1000}, \quad l = 1, 2, \dots, n \quad (18)$$

$$QSe_l = \frac{Pa \cdot NP_l \cdot Ec_l - Pl_l}{1000}, \quad l = 1, 2, \dots, n \quad (19)$$

Estimations for particulate matter, $PM_{2.5}$ (particles smaller than 2.5 μm and includes acids, organic chemical, metals, soil and dust), and carbon emissions during the combustion of different feedstocks can found in several sources of literature. For example, the $PM_{2.5}$ emissions from wheat and rice straw combusted at a low efficiency range from 4.7 g/kg to as high as 13 g/kg respectively [3–5,42]. The particulate matter and CO_2 emission reductions, PMR and CO_2R , as a result of the prevention of field burning can therefore be calculated,

$$PMR_l = 4.7 \cdot DWheat_l + 13 \cdot DRice_l, \quad l = 1, 2, \dots, n \quad (20)$$

$$CO_2R_l = 1400 \cdot (DWheat_l + DRice_l), \quad l = 1, 2, \dots, n \quad (21)$$

The income, $Income$, and profit, P , from the plant is determined from,

$$Income_l = \frac{Qc_l \cdot Sc_l \cdot 1000 + QSe_l \cdot Se_l \cdot 1000 + QSo_l \cdot So_l \cdot 1000}{1,000,000}, \quad l = 1, 2, \dots, n \quad (22)$$

$$P_l = Income_l - Ototal_l, \quad l = 1, 2, \dots, n \quad (23)$$

4.4. Goal deviations

Deviations from the goals can be finally determined from the following equations:

$$AWheat_l - DWheat_l = AWheat_l^{-d}, \quad l = 1, 2, \dots, n \quad (24)$$

$$ARice_l - DRice_l = ARice_l^{-d}, \quad l = 1, 2, \dots, n \quad (25)$$

$$DWheat_l + DRice_l = \frac{Pa \cdot NP_l \cdot Pc_l}{1,000,000}, \quad l = 1, 2, \dots, n \quad (26)$$

$$PP + PP_l^{+d} - PP_l^{-d} = \frac{Capex + Capex_l^{+d} - Capex_l^{-d}}{Income_l - Ototal_l}, \quad l = 1, 2, \dots, n \quad (27)$$

$$LEC + LEC_l^{+d} - LEC_l^{-d} = \frac{(Ototal_l - Oe_l * 1,000,000)}{Pa \cdot 0.35 \cdot NP_l \cdot Pc_l}, \quad l = 1, 2, \dots, n \quad (28)$$

$$LCOE + LCOE_l^{+d} - LCOE_l^{-d} = \frac{(Ototal_l * 1,000,000)}{Qe_l * 1000}, \quad l = 1, 2, \dots, n \quad (29)$$

5. Case studies

Two case study examples are now used to demonstrate and evaluate the model: deployment of pyrolysis plants in three small rural villages (Case 1) and across five districts of Punjab (Case 2). The model is solved for the different case study applications using LINGO[®], which is a well established optimisation software package for carrying out linear, mixed integer and goal programming calculations [43]. Site specific data has been gathered for the candidate sites including area of location, feedstock availabilities and feedstock cost. Stakeholder requirements, in the form of goals and goal deviation weightings, for the case studies have been captured from three anonymous investors, and farmers and village heads from the Punjab villages of Hussainpur, Ladal and Khuaspura. The case studies are modelled with both the farmer and investor weightings and by applying no weightings; thus enabling the sensitivity of the results to be evaluated. These goal deviation weightings are summarised in Table 1. Note that some goal deviations have a negative weighing. This indicates that a negative deviation is a desirable attribute, e.g. a lower payback period.

To model the case studies, several assumptions are made about the plant economics and where possible data has been collected. The operating costs of the pelletiser, pyrolysis reactor and diesel engine are assumed to be 20% of the capital cost per annum. In order to store the raw material, a warehouse could be leased at a cost of approximately \$14,000 per kilo tonne per annum (ktpa). The cost of transporting the raw material, O_t , is determined for a tractor and trolley, transporting a load, t_l , of 1.5 tonnes per journey at a speed, t_s , of 15 km/h, consuming fuel, f_c , at 0.71 l/km. The cost of diesel, cd , is taken at the 2013 cost in India of 0.85 \$/l. The wage cost for a driver, cw , is assumed to be 0.15 \$/h. Research indicates that a 20 kg/h pyrolysis unit manufactured in India will cost in the region of \$18,500 with costs increasing to \$37,000 for a 100 kg/h unit. A 20 kW diesel engine purchased in Punjab costs \$5550, a larger 100 kW engine costs upwards of \$27,750. Additional components for the pyrolysis plant (heaters, motors, control unit, etc.) cost \$30,500. The cost of manufacturing a 100 kg/h pelletiser would be around \$1850. The capital costs of the individual components are defined as follows for use in the goal programming model:

$$Cp_l = \frac{(Pc_l \cdot 46 + 925) \cdot NP_l}{1,000,000}, \quad l = 1, 2, \dots, n \quad (30)$$

$$Ce_l = Ec_l \cdot NP_l \cdot 0.00028, \quad l = 1, 2, \dots, n \quad (31)$$

$$Cpyro_l = \frac{((Pc_l \cdot 230 + 13875) \cdot NP_l)}{1,000,000}, \quad l = 1, 2, \dots, n \quad (32)$$

$$Ca_l = 1.65 \cdot NP_l, \quad l = 1, 2, \dots, n \quad (33)$$

Table 1

Importance weightings of goal deviations from the perspective of farmers and investors.

Deviation variable	Farmers	Investors	No weighting
$AWheat^{+d}$	1	25	1
$AWheat^{-d}$	100	50	1
PP^{+d}	10	30	1
PP^{-d}	-10	-30	1
$Capex^{+d}$	10	50	1
$Capex^{-d}$	-10	-50	1
LEC^{+d}	20	12	1
LEC^{-d}	-20	-12	1
$LCOE^{+d}$	10	5	1
$LCOE^{-d}$	-10	-5	1

Table 2
Financial inputs for the goal programming model.

Constraint	Units	
Plant availability	h/year	6570
Sale price of electricity	\$/kWh	0.3
Sale price of oil	\$/kg	0.65
Sale price of char	\$/kg	0.04
Percentage loan of capital cost	%	0.8
Period of loan	Years	20
Interest rate on loan	%	0.05
Capital subsidy	%	0
Cost of diesel	\$/kg	1.04

Several other financial assumptions have been made in order to demonstrate the model and these are summarised in Table 2.

5.1. Case study 1: small scale village plants

The majority of India's population lives in the countryside and is sustained by agriculture. In 2008, 47.5% of the rural population did not have access to electricity. Tens of thousands of villages remain without electricity today and, due to their remote location and low power consumption, it is not financial viable for them to be connected to the electricity grid. Even villages with electricity suffer from regular blackouts [44–46]. This case study investigates the feasibility of deploying small scale pyrolysis plants in three villages (Hussainpur, Ladal and Khuaspura) in Punjab's Rupnagar district. These small villages have around 100–300 acres of farmland that is used to grow rice and wheat straw and the villages are located several kilometres from the nearest town. They are connected to the grid but experience around 3–5 h of power cuts a day and have no backup generators. Information on feedstock availabilities and costs, and average distance to transport feedstocks is shown in Table 3. Based on feedback from the farmers and investors, suitable goals for a pyrolysis project are specified in Table 4.

5.2. Case study 2: large scale district plants

The Indian state of Punjab has a population of 33 million people and contains 22 districts. Agriculture is the main industry in Punjab producing 20% and 11% of India's wheat and rice respectively. Between 1995 and 2005, the electricity consumption of Punjab doubled with an annual growth rate of 15%. Research by Singh et al. [1,2] shows that the available waste feedstocks in Punjab's districts have an energy generation potential of 235 Tj. They concluded that the most promising regions for generating energy from waste straw are Moga, Ludhiana, Fatehgarh Sahib, Patiala and Sangrur. This case study investigates the feasibility of deploying pyrolysis plants across these five districts of Punjab and what the optimal number and size of plants would be. Table 5 shows the feedstock availabilities in these five districts. The specified goals for this case study are provided in Table 6.

Table 3
Cost, availability and distance of feedstock in the villages of Hussainpur, Ladal and Khuaspura.

Locations data	Cost of wheat (\$/kg)	Cost rice (\$/kg)	Available wheat (ktpa)	Available rice (ktpa)	Average distance to transport straw (km)	Total area (km ²)
Hussainpur	0.037	0.022	0.375	0.45	2.9	60
Ladal	0.044	0.022	0.2	0.5	3.4	80
Khuaspura	0.037	0.022	0.25	0.3	2.4	40

Table 4
Goal targets for case study 1.

Goal	Unit	Value
Payback period	Years	6
Capital cost	million\$	0.09
Production (levelised) cost of bio-oil	\$/kg	0.6
Levelisedcost of electricity	\$/kWh	0.28

6. Results and discussion

The results from the goal programming model for the two case study examples are shown in Tables 7 and 8. The sensitivity of the results for each proposed location is illustrated by various importance weightings for the goals; no weightings and weightings allocated by farmers and investors.

The optimal design of the supply chain for case study 1 (deployment of pyrolysis systems in villages) is significantly different from a farmer's perspective in comparison to an investors. Whilst the number of plants is insensitive to different goal deviation weightings, the recommended size of a plant and its components vary considerably. Based on the farmers' opinions, the plant should process around 20–30 kg/h and be coupled to a 75–125 kW diesel generator. This results in a large quantity of electricity being produced at a lower levelised cost of electricity. From an investor's perspective, a single larger 100 kg/h pyrolysis unit producing purely bio-oil and bio-char is the optimal specification for a plant. This recommended plant set-up is attributed to the resulting decrease in payback period. Whereas the farmer weightings produce payback periods ranging from 6.5 to 4.2 years, the investor weightings result in a payback period as low as 1.1 years. The ranking of the locations is relatively insensitive to the weightings. Hussainpur is the least preferred location among the three villages and Khuaspura is the preferred location based on the farmer and investor weightings.

On a district scale, case study 2, the differences among the results for farmer and investor goal weightings are less significant. For each location, several plants each sized at the maximum 100 kg/h processing capacity with a coupled diesel generator in the region of 100 kW are recommended. Fatehgarh Sahib is determined to be the preferred location among the five most promising districts in Punjab for the deployment of pyrolysis plants. One difference is the number of plants suggested for each location. Fewer plants are suggested based on the investor weightings as this reduces capital costs at the expense of a slightly higher levelised cost of electricity and payback period. For no goal weightings, a large number of small scale plants are recommended. While impractical, this illustrates the goal programming model's capability to determine the optimal decisions in order to best meet stakeholder specified goals.

The goal programming model demonstrates that there is an economically feasible solution for deploying pyrolysis systems on both a small and large scale in India. Whilst farmers would prefer a

Table 5
Cost, availability and distance of feedstock in the districts of Moga, Ludhiana, Fatehgarh, Patiala and Sangrur.

Locations data	Cost of wheat (\$/kg)	Cost of rice (\$/kg)	Available wheat (ktpa)	Available rice (ktpa)	Average distance to transport straw (km)	Total area (km ²)
Moga	0.044	0.027	150	250	18	2230
Ludhiana	0.033	0.021	300	600	23	3787
Fatehgarh	0.033	0.019	125	250	22	3418
Patiala	0.055	0.033	250	500	24	3988
Sangrur	0.037	0.037	400	800	21	3004

Table 6
Goal targets for case study 2.

Goal	Unit	Value
Payback period	Years	3
Capital cost	million\$	1.85
Production (levelised) cost of bio-oil	\$/kg	0.4
Levelised cost of electricity	\$/kWh	0.28

small scale system that is predominately used for generating electricity (up to 780 kWh/year), such a system would only make a \$0.01 million profit per annum. Substantially larger profits are achievable by selling bio-oil – provided there is enough demand – as even small scale systems can produce bio-oil at a levelised production cost as low as 0.18 \$/kg. In comparison, the purchase price of diesel in India is around 0.9 \$/kg. Pyrolysis is a more attractive investment on a large scale as profits as high as \$0.8 million are achievable. However, diesel generators are an expensive method of producing electricity and this is reflected in the levelised costs of electricity: 0.25–0.50 \$/kWh for a small scale plant and 0.14–0.28 \$/kWh for a larger system. Therefore, local governments need to provide appropriate subsidies and supportive mechanisms to increase the uptake of pyrolysis systems. This will encourage farmers to gather waste straw and promote more sustainable agricultural practices. Introduction of suitable policies will also drive technology cost reductions and establish pyrolysis as a viable approach to reducing the practice of open field burning and generating alternative bioenergy products from agro-wastes. Growth in the waste to energy sector in India will also have major implications to other countries such as China where open field burning is also widely practiced.

The results are highly dependent on the stakeholder goals and weightings, and the assumptions that have made in order to demonstrate the model. The market values assumed for the bio-fuels will be highly influential when determining the plant's feasibility; in particular bio-oil as it is a relatively un-established fuel. Furthermore, data on the pyrolysis plant's cost and performance are based on preliminary findings from prototype systems and are assumed to be valid for the entirety of the plant's operational life. Additional work on the prototype systems will be to characterise their long term performance. The gas from a pyrolysis plant has not been model in this study. However, there is scope to use the gas in a duel fuel engine to complement the bio-oil/diesel

blend. The advantage of goal programming is that different assumptions and stakeholder requirements can be easily evaluated. The case studies have been used to demonstrate that the model can quickly provide a techno-economic feasibility assessment of an optimised plant for different requirements and 'what if' scenarios. For example, fluctuations in market prices for fuels and how the plant might be financed can be easily simulated and weightings can be used to provide an importance to goal targets. By incorporating importance weightings for the goals, targets can even be improved. In this model, goals have been chosen for capital cost, payback period and production costs of bio-oil and electricity. However the model can be adapted to enable different goals to be specified. Given this flexibility, in further work the model should be applied to various case scenarios with additional stakeholder opinions taken into account, such as plant developers and municipalities. To a further extent, the model has implications and applications in other waste to energy decision-making problems.

7. Conclusion

We have outlined a goal programming model for optimising the supply chain for deploying pyrolysis plants in Punjab, India based on stakeholder requirements and opinions. To demonstrate the model we have applied it to two alternative case scenarios: pyrolysis plant deployment at a village and district level.

The case studies reveal that the deployment of pyrolysis plants generating bio-fuels from waste straw in small villages in Punjab is techno-economically feasible and wider deployment across the districts of Punjab will further reduce plant payback periods. The district of Fatehgarh Sahib is determined to be the ideal candidate location for a plant in Punjab. However, these results are based on the preliminary findings from a prototype pyrolysis system which are assumed to be valid and representative of the long term performance.

We conclude that the mixed integer non linear goal programming model outlined in this study can successfully recommend the optimal decisions for deploying pyrolysis plants in Punjab, India. Furthermore, the incorporation of stakeholder requirements into the decision rationale, in the form of target goals and weighted goal deviations, is considered to be an improved method for supply chain design in the field of bio-energy in comparison to the more conventional approach used in the literature; i.e. mixed integer programming.

Table 7
Goal programming results for case study 1: pyrolysis deployment in rural villages.

Criteria	Location	Weightings	Hussainpur			Ladal			Khuaspura		
			None	Farmer	Investor	None	Farmer	Investor	None	Farmer	Investor
Decision variables	Ranking	–	3	3	3	1	2	2	2	1	1
	DWheat	ktpa	0.13	0.12	0.21	0.14	0.20	0.20	0.13	0.16	0.25
	DRice	ktpa	0.00	0.00	0.45	0.00	0.00	0.46	0.00	0.02	0.30
	Pc	kg/h	20	18	100	22	30	100	20	27	84
	Ec	kW	35	75	25	39	127	25	35	117	21
	NP	–	1	1	1	1	1	1	1	1	1
Achieved	PP	Years	6.0	6.5	1.1	6.0	4.2	1.2	6.0	4.8	1.3
	Capex	million\$	0.06	0.07	0.08	0.06	0.09	0.08	0.06	0.09	0.07
	LCOO	\$/kg	0.37	0.46	0.18	0.38	0.42	0.19	0.37	0.41	0.19
	LCOE	\$/kWh	0.28	0.24	0.49	0.28	0.24	0.50	0.28	0.24	0.50
Additional outputs	O&M _{total}	million\$/year	0.06	0.12	0.08	0.07	0.20	0.08	0.06	0.19	0.07
	Income	million\$/year	0.07	0.13	0.15	0.08	0.22	0.15	0.07	0.20	0.13
	P	million\$/year	0.01	0.01	0.07	0.01	0.02	0.07	0.01	0.02	0.06
	CO2R	tpa	198	178	986	214	300	986	198	270	825
	PMR	tpa	0.62	0.56	6.82	0.67	0.94	6.88	0.62	1.01	5.08
	Qse	kWh/year	195	465	0	220	783	0	195	727	0
	QSo	tpa	27	0	219	28	0	219	27	0	183

Table 8
Goal programming results for case study 2: pyrolysis deployment in Punjab districts.

Criteria	Location	Moga			Ludhiana			Fatehgarh Sahib			Patiala			Sangrur			
		Weightings	None	Farmer	Investor	None	Farmer	Investor	None	Farmer	Investor	None	Farmer	Investor	None	Farmer	Investor
Decision variables	Ranking	–	1	3	3	5	2	2	1	1	2	4	4	5	3	5	4
	DW/heat	–	1.62	0	0	1.84	0	0	1.83	0	0.74	0	0	0	1.53	1.97	1.09
	DRice	–	0.22	2.63	1.25	0	2.63	1.30	0	2.63	1.10	0	2.63	0	0	0	0
	Pc	–	16	100	95	16	100	99	15	100	16	100	100	100	16	100	83
	Ec	–	8	98	79	7	93	71	7	91	8	103	35	7	112	87	87
Achieved	NP	–	18	4	2	18	4	2	18	4	18	4	1	15	3	2	2
	PP	–	3.00	0.51	0.72	3.00	0.51	0.71	3.00	0.51	3.00	0.51	1.40	3.00	0.53	0.71	0.71
	Capex	–	0.93	0.40	0.19	0.93	0.40	0.18	0.93	0.39	0.93	0.41	0.08	0.93	0.31	0.18	0.18
	LCOO	–	0.37	0.21	0.21	0.35	0.19	0.19	0.34	0.18	0.37	0.23	0.22	0.35	0.24	0.25	0.25
	LCOE	–	0.28	0.14	0.21	0.28	0.13	0.21	0.28	0.13	0.21	0.28	0.14	0.28	0.14	0.18	0.18
Additional outputs	O&M _{total}	–	0.25	0.35	0.22	0.24	0.32	0.20	0.23	0.31	0.25	0.38	0.11	0.20	0.32	0.21	0.21
	Income	–	0.56	1.14	0.48	0.55	1.10	0.46	0.54	1.09	0.56	1.17	0.17	0.46	0.91	0.47	0.47
	P	–	0.31	0.79	0.26	0.31	0.78	0.26	0.31	0.77	0.31	0.80	0.06	0.26	0.59	0.26	0.26
	CO2R	–	2759	3942	1869	2753	3942	1882	2749	3942	2756	3942	986	2300	2957	1635	1635
	PMR	–	10.45	34.16	16.20	8.63	34.16	16.31	8.61	34.16	17.73	34.16	8.54	7.21	9.26	5.12	5.12
Qse	Qse	–	436	1931	721	396	1781	645	370	1739	439	2051	68	337	1724	869	869
	QSo	–	640	881	405	638	883	410	638	884	640	879	216	533	628	334	334

Due to the complexity of the supply chain for renewable energy systems, inappropriate strategic decisions are often made leading to project failure. This is particularly problematic in the bio-energy sector as a result of complex logistics. The benefits of a goal programming model over traditional business case development and evaluation methods is that the key decisions for plant sizing, site location, feedstock type and supplier selections are simultaneous made in order to establish the optimal design for the downstream, conversion process and upstream supply chains. Thus, we have addressed the need for a tool that takes a holistic approach to bio-energy supply chain design, rather than making decisions at a single stage of the logistical supply chain. We believe that the goal programming method for optimal decision-making along the entire supply chain to be highly promising for bio-energy developments and should be utilised by plant developers, waste authorities and other stakeholder currently involved in the implementation of bio-energy conversion technologies.

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