Combining Monte Carlo simulations and experimental design for incorporating risk and uncertainty in investment decisions for cleantech: a fast pyrolysis case study

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Abstract

The value of phytoextracting crops (plants cultivated for soil remediation) depends on the profitability of the sequential investment in a conversion technology aimed at the economic valorization of the plants. However, the net present value (NPV) of an investment in such an innovative technology is risky due to technical and economic uncertainties. Therefore, decision makers want to dispose of information about the probability of a positive NPV, the largest possible loss, and the crucial economic and technical parameters influencing the NPV. This paper maps the total uncertainty in the NPV of an investment in fast pyrolysis for the production of combined heat and power (CHP) from willow cultivated for phytoextraction in the Belgian Campine. The probability of a positive NPV has been calculated by performing Monte Carlo simulations. Information about possible losses has been provided by means of experimental design. Both methods are then combined in order to identify the key economic and technical parameters influencing the project's profitability. It appears that the case study has a chance of 87 % of generating a positive NPV with an expected value of 3 million euro (MEUR), whilst worst case scenarios predict possible losses of 7 MEUR. The amount of arable land, the biomass yield, the purchase price of the crop, the policy support and the product yield of fast pyrolysis are identified as the most influential parameters. It is concluded that both methods, i.e. Monte Carlo simulations and experimental design, provide decision makers with complementary information with regard to economic risk.

Keywords

Economic risk, Monte Carlo simulations, Experimental design, Cleantech, Pyrolysis, Phytoremediation

1. Introduction

A vast area of agricultural land in the Belgian Campine has been moderately contaminated with zinc (Zn), cadmium (Cd), lead (Pb) and copper (Cu) (Kuppens and Thewys 2010). Hence, the polluted farmland should not be used for the cultivation of crops for human or animal consumption, but instead can be employed for the growth of energy crops that simultaneously take up heavy metals from the soil (Khalid et al., 2016; Xiong et al., 2016). The use of such plants for metal removal by concentrating them in the harvestable parts is called *phytoextraction* (Ensley 2000). The latter has an impact on the farmer's income (Thewys and Kuppens 2008; Kuppens and Thewys 2010). For instanse, Yang et al., 2017 found that with phytoextraction of the contaminated leaves of tobacco farmers are able to generate animal feed, helping to reduce total cadmium concentration in soil, and produce income for farmers. The economic feasibility of phytoextraction can be enhanced by the valorization of biomass (Kuppens et al. 2010; Jiang et al., 2015).

Willow cultivated in short rotation appears to have good phytoextraction potential on the sandy, acidic soils of the Belgian Campine (Vangronsveld et al. 2009). The lignocellulosic chemical composition of short rotation willow motivates the choice for thermochemical conversion technologies (combustion, gasification and pyrolysis). Fast pyrolysis prevents metals from volatilization because of its low process temperature compared to combustion and gasification (Stals et al. 2010). For small scales of short rotation willow conversion fast pyrolysis is also more profitable than gasification or combustion (Kuppens and Thewys 2010). Because of these two reasons fast pyrolysis is a better conversion technology for the valorization of the phytoextracting willow compared to combustion and gasification (Jiang et al. 2015).

Entrepreneurs, however, are only willing to invest in such an innovative conversion technology if there are prospects of return on investment, i.e. if the net present value (NPV) of the cash flows generated by the investment is positive. Recently, the techno-economic assessment (TEA) of fast pyrolysis in biobased industries has been of growing interest for many researchers in different themes. Considering a fast pyrolysis and bio-oil fractionation system, Hu (2015), for example, compared the results of TEA for three biobased products including biochemicals, hydrocarbon chemicals and biofuels and identified the latter as the less profitable option for a bio-refinery. Furthermore, Brown et al. (2013) estimated the minimum fuel selling price of gasoline and diesel produced via fast pyrolysis and hydroprocessing and concluded that they have the potential to be more profitable than petroleum. In addition, the economic potential of phytotechnologies is gaining importance as well. Rentsch et al. (2016) highlighted the economic feasibility of producing germanium through phytomining. Novo et al. (2015) studied the economic viability of Rhenium phytomining and expected a profit of 3906 US$ ha^{-1} $harvest^{-1}$ from the recovered Rhenium under phytomining. In another research, Ni phytomining was identified as a highly profitable agricultural technology for two generalised production systems from the USA and Albania (Nkrumah et al., 2016). Van der Ent et al. (2013) also showed the potential of the extraction of residual nickel by hyperaccumulators in generating income throughout the phytomining process.

The prediction of the NPV is by definition associated with uncertainty about the level of costs, prices and product yields, among others (Kazantzi et al. 2013). Another source of uncertainty when comparing TEA results comes from the differences in the approach employed among scholars to determine the values of technical and market variables. (Brown and Wright, 2014). Therefore, instead of using static values for the parameters of the economic model, they need to be represented by suitable probability distributions (Li et al., 2015). One of the most common ways to conduct uncertainty analysis is through Monte Carlo simulations (Hsu, 2012) which randomly produce samples of the parameter to analyse the level of uncertainty in the results. Considering the probabilities on a subjective basis in the Monte Carlo simulations bring some doubt over suitability of the method. Gadallah 2011) and Van Groenendaal and Kleijnen (1997) propose methods from design of experiments (DOE) as an alternative for Monte Carlo simulations in order to identify the most influential factors on profitability of a project without considering probability distributions. To our knowledge, experimental design and Monte Carlo simulations have never been combined in techno-economic assessments before, and especially not within the domain of pyrolysis of phytoextracting crops. In order to identify the key economic and technical parameters influencing the project's profitability of fast pyrolysis processes, the results from both methods are compared. This should help us to provide more robust advice on risk reduction strategies before investing in the fast pyrolysis clean technology. After all, Yatim et al. (2017) emphasize that lack of knowledge regarding risks and uncertainties related to the biomass industry is often mentioned as one of the reasons for the slow growth of such industries and innovative technologies.

2. Methodology

Before mapping the economic risk, a techno-economic model has been built for the prediction of the outgoing and incoming cash flows from an investment in fast pyrolysis. During this techno-economic assessment it became clear that the values of expenditure and revenue items are highly uncertain. Therefore, Monte Carlo simulations have been performed in order to check the sensitivity of the NPV for changes in the input variables of the techno-economic model and to predict the probability of a positive NPV. Monte Carlo simulations, however, require knowledge about the probability distribution for the values of the input variables, which is often absent. As an alternative Plackett-Burman designs have been constructed following the approach of Van Groenendaal and Kleijnen (1997) and Van Groenendaal and Kleijnen (2002).

2.1 Techno-economic model

The techno-economic model of fast pyrolysis serves as an input for a larger cost-benefit analysis of phytoextraction as a whole. Phytoextraction is often proposed as a low cost remediation technology with the longer time frame required for reclamation (compared to traditional excavation techniques) as its main disadvantage. If phytoextraction could be combined with a revenue earning operation its time constraint might become less important. The repercussions of phytoextraction on the farmer's income can be based on the "income per hectare per year" as a measurement concept (Vassilev et al. 2004; Kuppens and Thewys 2010), which is determined by:

- the costs involved with cultivating phytoextracting crops;

- the opportunity cost of switching from current activities to phytoextraction;
- the income from biomass valorization to recover the costs of phytoextraction;
- the potential higher income from crops for human consumption after phytoextraction.

During phytoextraction a farmer receives a certain income by selling the produced phytoextracting biomass. It is expected that the income during phytoextraction is much lower than the income that can be earned by the current activities of the farmers in the Campine (mainly from dairy cattle rearing). This lost income can be considered as the cost of phytoextraction and depends both on the level of income during soil reclamation and the time required for soil sanitation (Vassilev et al. 2004; Kuppens 2012).

After phytoextraction, the cleaned up soil can be used for the cultivation of high value vegetables (Vassilev et al. 2004; Lewandowski et al. 2006). It is expected that these vegetables generate an income that is higher than the income from current activities on polluted soils. This income can be considered as the benefit of phytoextraction. By discounting the costs and benefits over the total time period, one arrives at the net present value (NPV) of phytoextraction.

Assessing the techno-economic potential of fast pyrolysis contributes to the determination of the the farmer's income during phytoextraction (Y_{phyto}) with willow. The private cost of phytoextraction (C_{phyto}) can then be approached by deducting the farmer's income during phytoextraction (Y_{phyto}) from the currently income from rearing dairy cattle (Y_{dairy}) (see Eq. 1).

$$C_{phyto} = Y_{dairy} - Y_{phyto} \tag{1}$$

with: C_{phyto} = private cost of phytoextraction (EUR ha^{-1} a^{-1})

Y_{dairy} = income of dairy cattle rearing (EUR ha^{-1} a^{-1})

Y_{phyto} = income during phytoextraction (EUR ha^{-1} a^{-1}).

The farmer's income during phytoextraction is further defined as the difference between the turnover of the sold willow and the costs of cultivating and harvesting it (see Eq. 2) (Kuppens and Thewys 2010; Kuppens 2012):

$$Y_{phyto} = q_{willow} \cdot (p_{willow} - c_{willow}) \tag{2}$$

with: q_{willow} = yearly amount of sold willow (t ha^{-1} a^{-1})

p_{willow} = unit willow price (EUR t^{-1})

c_{willow} = unit cost of cultivating and harvesting willow (EUR t^{-1})

The unit willow price is the price that a farmer receives for selling one tonne of willow to an investor in renewable energy. The price that an investor is willing to pay for obtaining one tonne of willow depends on the "net present value" (NPV), which is today's value of current and future cash flows generated by the investment using a predetermined discount rate that accounts for the opportunity cost of money related to not employing the capital in alternative investments (see Eq. 3):

$$NPV = \sum_{n=1}^{T} \frac{CF_n}{(1+i)^n} - I_0 \tag{3}$$

with: T = life time of the investment, i.e. 20 years (every year is indexed by the symbol "n");

CF_n = cash flow (or after tax difference between revenues and expenditure) in year n;

i = discount rate, i.e. 9 % (Ochelen and Putzeijs 2008);

I_0 = investment expenditure in year 0.

The cash flow in year n is the sum of the after tax $(1 - \tau)$ difference between revenues in year n (R_n) and expenditure in year n (E_n), and the tax shield caused by depreciation (D_n) which lowers yearly taxable profits and hence the expenditure paid by the investor for taxes in year n (see Eq. 4):

$$CF_n = (1 - \tau) \cdot (R_n - E_n) + \tau . D_n \tag{4}$$

The prediction of revenues and expenditure in each year is based on literature and checked with expert opinion where possible. Most of the times a range of values has been found for the revenue and expenditure items which causes economic risk. For each item base-case values have been determined as the average of the most prevalent values (excluding outliers) or as the most current figure available.

These base-case values however are quantities that will take some value in the future, but that are unknown at the moment of decision-making because of a lack of knowledge: i.e. the uncertainty is expert based or *epistemic* (Aven 2003).

2.2 Monte Carlo simulations

Decision makers facing uncertainties in key assumptions of these yearly cash flows need more information than just the expected value. An assessment of the uncertainty is required which can be measured by probabilities (Aven 2003; Hertz 1979). Besides, information about the impact of a change in the assumptions on the predicted NPV is required. Often this is dealt with by means of partial sensitivity analysis or by developing best and worst case scenarios. However, if base-case assumptions are more likely to occur than the extremes of the ranges found in literature, then best and worst case scenarios contain little information value because they require the joint occurrence of independent low-probability events. Monte Carlo analysis overcomes this problem by taking into account probability distributions for important uncertain quantitative assumptions (Vose 2000; Boardman et al. 2006). Furthermore, Monte Carlo simulations have the capability to analyse the level of uncertainty by means of probability distributions as a replacement for the static values of the parameters for the techno-economic model (Hsu 2012; Greenland 2001). Monte Carlo simulations are one of the most straightforward ways to apply uncertainty analysis (Li, 2015). However, whenever one wants to predict the product yields of the pyrolysis process, one can use the technique of artificial neural networks (ANN) as has been done by Aydinli et al. (2017) and Karaci et al. (2016). ANN is a powerful modelling tool for predictive purposes. However, ANN can be considered as a black box that provides little explanatory insight into the contributions of the independent variables in the prediction process (Karaci et al. 2016; Olden et al. 2004). The focus here actually is not on the prediction of the NPV, but on the identification of the uncertainties that contribute the most to the variance of the NPV as a consequence of this uncertainty. Therefore, Monte Carlo simulations in combination with experimental design has been preferred above the use of ANN. Monte Carlo analysis has been integrated in the "unifying approach" for expressing economic risk proposed by Aven (2003); Aven et al. (2004):

1. The overall system performance measure has been identified as the NPV of the investment in a fast pyrolysis plant;
2. A deterministic model of the system linking the system performance measure (NPV) and observable quantities on a more detailed level (low-level) has been determined by means of the techno-economic model;
3. Collect information about low-level observable quantities by means of literature review and expert opinions. Use probabilities to express uncertain observable quantities. The uncertain variables have been identified according to the following principles:
    a. some variables are uncertain by definition, e.g. market prices;
    b. other variables might have a very large impact on the NPV, and should be incorporated in any risk analysis even if their values are only slightly uncertain;
    c. after selecting the variables following principles (a) and (b), their impact on the variability of the NPV is investigated and the variables which explain the largest part of the variability of the NPV are withheld for performing Monte Carlo analysis.
4. Calculate the probability distribution of the NPV given the assumed probability distributions of the determining variables and predict the net benefits taking into account these distributions, which has been executed by means of Monte Carlo simulations.

Triangular probability distributions have been chosen to express uncertainty for the intuitive nature of its defining parameters (Vose 2000). The triangular distribution is an adequate solution when literature is insufficient for deriving probabilities (Haimes 2004). It is also the most commonly used distribution for modeling expert opinion (Vose 2000). All possible correlations between input variables have been built in the cost-benefit model, so that the remaining uncertain variables can be considered as independent and the construction of correlated variables in the Monte Carlo simulations is not appropriate (Savvides 1994). For instance, it is reasonable to expect some negative covariance between unit costs and produced quantity due to expected economies of scale. When probability distributions are defined for these two variables it would be interesting to restrict the random generation of values for the two variables, so that unrealistic scenarios (e.g. when both unit costs and produced quantity are high) are avoided (Savvides 1994). In this case study however, economies of scale are assumed in the total plant cost of an investment: the total plant cost increases at a decreasing rate with increasing quantity, i.e. the specific investment cost per unit produced decreases with increasing production capacity. This correlation between investment cost and quantity produced has been built in the techno-economic model by the structure defined for investment equations ($C = aQ^d$) developed during a meta-analysis of investment costs for a pyrolysis plant. With this structure there is already a correlation present in the model between the produced quantity Q and the investment cost C which reflects the assumption of economies of scale. The only uncertainty remaining is about the exact level of the constant a and the exponent d in this equation, which is independent of the produced quantity Q but rather is technology dependent. Therefore it is not appropriate to construct an extra correlation between a and Q or d and Q, because then we would be incorporating economies of scale twice.

In step 4 Oracle's Crystal Ball software has been used to perform 10,000 Monte Carlo simulation runs, which results in a distribution of the NPV. The underlying data have finally been used for constructing a regression meta-model, whereby the NPV is modeled in terms of a linear combination of the input variables representing the main effects. The meta-model thus is a simplified approximation of the discounted cash flow model. The resulting equation can be used to have a quick glance at the most important variables and to help decision makers. Decision makers can use this equation in order to get a first estimate of the economic feasibility.

Another possible approach to deal with uncertain cash flows, is the use of a risk-adjusted discount rate. Many economists, however, argue that the risk-free discount rate should be used for Monte Carlo simulations and scenario analysis in order to avoid double-counting, as the risk aspects of the NPV are already summarized in the generated distribution (Aven 2003).

2.3 Plackett-Burman design

Monte Carlo simulations require knowledge about the distribution function (probability distribution) of the values of the relevant variables in the techno-economic model. Information with respect to these probabilities is often absent, and the best way one can do is to assign probabilities on the basis of their own opinion based on experience. Because the probabilities used in the Monte Carlo simulations are estimated on a subjective basis expressing our degrees of belief, Van Groenendaal and Kleijnen (1997) doubt the usefulness of Monte Carlo simulations. They propose methods from design of experiments (DOE), which is often used in industrial research, as an alternative for Monte Carlo simulations, to provide information on which factors or independent variables can make an investment project "go wrong", without requiring knowledge of probability distributions. These independent variables are the uncertain variables identified in step 3 of the unifying approach expressing economic risk, as explained in section 2.2. Hence, the independent variables of the experimental design are the same as the uncertain variables for which probability distributions have been defined in the Monte Carlo simulations. Because Van Groenendaal (1998) expects that decision makers are mainly interested in information in what can go wrong, he suggests to analyse changes in the values of independent variables that have a negative impact on the dependent variable. The latter is the NPV, i.e. the overall system performance measure determined in step 1 of the unifying approach expressing economic risk. To determine these negative effects the first step is to apply a one-factor-at-a-time sensitivity analysis. It is assumed that every factor or independent variable takes on either one of two values: -1 if the independent variable is "off" and +1 if the independent variable is "on". In other words, +1 corresponds to the base-case value of the corresponding independent variable, whereas -1 stands for the value that has a negative influence on the dependent variable. In DOE the effect of changes in the value of the uncertain independent variables on the NPV, i.e. the dependent variable is thus obtained by simulating the extreme points of the value ranges, and estimating a linear regression meta-model to detect which independent variables are important (Van Groenendaal and Kleijnen 1997).

The most prevalent experimental designs are *one-factor-at-a-time*, *full factorial designs*, and *fractional designs*. Changing one factor at a time ignores combined effects. Full factorial designs allow estimating all main effects. Full factorial designs however have the disadvantage that it requires substantial computer time. Therefore, fractional designs (e.g. Plackett-Burman designs), in which some independent variables are kept constant while others alter, have been developed to limit the number of simulations and thus save labor. For instance, given k independent variables and with every independent variable at two levels only, it requires 2^k simulation runs for estimating k + 1 effects (i.e. k main effects plus the overall mean), thus ten independent variables require $2^{10} = 1{,}024$ simulations. It has been proved that with less observations (i.e. fractional designs with less simulation runs) the same information can be obtained: in principle k + 1 observations suffice to estimate k + 1 effects (Van Groenendaal and Kleijnen 1997). In other words, it suffices to simulate only a fraction 2^{k-p} of the 2^k possible observations so that $2^{k-p} \geq k + 1$. These designs are also called 2^{k-p} designs and they have a number of simulation runs equal to a power of two. However, when the number of independent variables or factors becomes large, the number of simulation runs is still large (Van Groenendaal 1998). A class of designs that allows a more gradual increase in the number of simulation runs is the *Plackett-Burman design* type (Plackett and Burman 1946), which requires a number of runs equal to a multiple of four. Thus for ten independent variables, a Plackett-Burman design with twelve runs can be used. Therefore in this article the Plackett-Burman design has been applied following the approach of Van Groenendaal and Kleijnen for constructing a meta-model for the dependent variable, i.e. the NPV, and compared to the results from Monte Carlo simulations. In order to really compare both meta-models, the same "independent variables" have been identified, i.e. if Monte Carlo simulations are performed for 10 uncertain variables, the same 10 variables are considered in the Plackett-Burman designs.

The results of the 12 runs of the Plackett-Burman designs required for 10 independent variables are represented in a table in which each column corresponds to one simulation run with a plus (+) sign reflecting the base-case value of the variable and the minus (-) sign reflecting the worst case value negatively impacting the NPV as the dependent variable. Each column hence can be interpreted as a scenario, some of which may make economic sense, others being less likely (Van Groenendaal 1998). The tables of design are constructed in such a way that each independent variable is replicated at its base-case value the same number of times that it is replicated at its worst case value. Any combination of values of two independent variables also appears the same number of times. In a final run all the independent variables take on their worst case value (Plackett and Burman 1946). Identifying the base-case with only plus signs, means that all other runs focus on conditions that jeopardize the investment project (Van Groenendaal and Kleijnen 1997).

The disadvantage of the NPV's meta-model based on Plackett-Burman (PB) designs is that it can lead to erroneous conclusions in the presence of interaction effects. Such interactions appear when a change in two or more independent variables has a synergistic effect on the dependent variable. For instance, the same change in the value of the available farmland (independent variable) can cause a different alteration of the NPV (dependent variable) whether or not combined with changes in the value of other independent variables that also play a role in the presence of economies of scale. In other words, the negative change in the NPV brought about by changing the amount of available farmland from its base case to its worst case value might differ in combination with a similar (i.e. from base to worst case) change in the value of the willow yield compared to a combination with a similar change in the value of the sales price of green power certificates. In the former case, both the available farmland and the willow yield simultaneously influence the economic scale of the pyrolysis plant, whereas in the latter case the sales price of the green power certificates has no influence on the realization of economies of scale. Meta-modelling the Plackett-Burman designs will only result in an approximation of the simulations model (i.e. the techno-economic discounted cash flow model), when there are no interactions between independent variables. A suggested solution for avoiding biased estimates, is to augment the Plackett-Burman design with the Box-Wilson foldover. Such a foldover is obtained by adding the opposite design matrix to the original design matrix, so that 24 instead of 12 simulation runs are executed (Van Groenendaal 1998). One such Box-Wilson simulation run can be obtained by changing the signs of the corresponding Plackett-Burman simulation run. For instance, in the first Plackett-Burman run (indicated by "PB1" in table 7), the independent variable "available farmland" has a positive sign which reflects that the value of this variable is set at its base-case value (i.e. 2,400 ha; cf. table 3). In the first simulation run of the Box-Wilson foldover, however, the "available farmland" has a negative sign so that its value in this simulation run corresponds to its worst case value (i.e. 650 ha; cf. table 3). By applying the Box-

Wilson foldover, an unbiased estimator of the main effects can be achieved (Van Groenendaal and Kleijnen 1997). Finally, the main effects are estimated by means of ordinary least squares regression using the NPV data of table 7. The meta-model that results from the Plackett-Burman and Box-Wilson designs is then compared to the model from Monte Carlo simulation.

The data concerning the independent and dependent variables have been generated by the techno-economic model in Excel. Next, the Monte Carlo simulations have been performed by means of the Excel add-in Crystal Ball. Furthermore, the simulations for the Plackett-Burman and Box-Wilson design have been executed by means of the same Excel as the one built for the techno-economic model. No additional software was needed to create the experimental design, as the latter is readily available in literature (see above). However, an input screen which is tailored to the experimental set-up has been developed in the same Excel in order to run the above mentioned simulations from the Plackett-Burman design and its Box-Wilson foldover. Finally, both the data from the Monte Carlo simulations and the experimental design are inserted into the statistical software package SPSS for running the meta-models.

3. Results

3.1 Base-case

In this section the base-case assumptions related to the process parameters, the investment expenditure and the yearly cash flows during the lifetime of the pyrolysis plant are briefly explained. Next the NPV and the underlying cost structure and main revenue items are clarified.

3.1.1 Fast pyrolysis of metal contaminated wood for the production of CHP

In the Belgian Campine more than 2,000 ha of farmland hold Cd concentrations exceeding guide values set by the Flemish Government (Schreurs et al. 2011). At least 650 ha of this farmland can be remediated by means of willow within a time span of more or less 40 years, although 2,400 ha is the most probable surface available for phytoextraction (with a maximum of 3,000 ha) (Kuppens et al. 2015). Cultivation of short rotation willow crops on 2,400 ha farmland would lead to an annual production of 19.2 kton dry biomass per year in the Belgian part of the Campine region, given an average biomass yield of 8 ton dry matter per hectare per year (Vangronsveld et al. 2009). Willow trees from a field experiment on a former maize field in Lommel (Belgium) had a Cd content of 24 mg kg^{-1} and 60 mg kg^{-1} (dry weight) in the twigs and leaves, respectively (Vangronsveld et al. 2009). This means that a fast pyrolysis plant that is operational during 7,000 hours per year (Bridgwater 2009a), will convert 2.7 ton dry biomass per hour.

During fast pyrolysis, biomass is rapidly heated in the absence of oxygen in a fluidized bed (Bridgwater 2012). This means that not real combustion, but only a thermal cracking of the long carbon molecules of the willow feedstock into smaller molecules takes place, resulting in the production of vapors and char (Diebold et al. 1999; Meier et al. 1999). Consequently, the vapors are rapidly quenched so that a dark brown liquid is formed with an energy content between 16 and 18 GJ/ton (Gust et al. 2005; Oasmaa and Meier 2005). This way, between 60 and 70 % of the original biomass weight can be converted into pyrolysis oil, whereas some 10 to 20 weight % is converted into a non-condensable biogas and another 10 to 20 weight % into the char which contains the heavy metals (Bridgwater et al. 2002). Lab-scale experiments on pyrolysis of willow samples from the field in Lommel showed that the Cd concentration of pyrolysis oil is only 0.9 ppm pyrolysis at temperatures of 723 K. Whenever the samples are pyrolysed at a high temperature of 823 K the Cd is strongly volatilised with Cd concentrations up to 16 ppm in the pyrolysis oil (Stals et al. 2010). The oil can be burnt in a static engine for the production of CHP (which appears to be more profitable than only electricity production) (Kuppens et al. 2015), whereas the biogas is used for internal energy requirements. It is currently not clear whether there exists an economically viable application for the residual char. A promising option is the production of active coal in combination with recycling and mining of the heavy metals from the char (Kuppens et al. 2015). This might enhance the NPV provided that the concentration of the heavy metals in the char is sufficiently high. Currently it is supposed that the heavy metal containing char needs to be landfilled. A simplified mass and energy balance for the case study can be found in figure 1. For a detailed description of its underlying assumptions, we refer to Kuppens (2012) and Kuppens et al. (2015).

[insert Fig. 1]

3.1.2 Investment expenditure

The investment expenditure consists of the expenditure for the pyrolysis plant and the investment cost of the CHP engine. As pyrolysis is a new technology, there are not a lot of cost data available (Rogers and Brammer 2012). Moreover, cost data for pyrolysis plants vary significantly (Uslu et al. 2008) and the capital cost of processes that have not been built are very uncertain (Bridgwater 2009b). Therefore, the proposed investment cost in year 0 (I_0) of the pyrolysis reactor is the result of a meta-analysis of the capital cost for an investment in fast pyrolysis (Kuppens 2012). During the meta-analysis existing estimates for the capital costs of pyrolysis plants have been inventoried. The found capital costs can be either point estimates (Van de Velden et al. 2008; Sorenson 2010) for a specific case or estimated by equations (Siemons 2002) that are a function of the plant's scale which already aggregate existing data on capital cost estimates. Regarding the point estimates, Peacocke, Bridgwater et al. (2006), for instance, set a "typical value" of 4 % of the total plant cost per year for maintenance and the same for overheads.

Rogers and Brammer (2009) also developed a point estimation method using transport zones while taking into account biomass availability. With regard to the equations, for example, Bridgwater et al. (2002) applied the percentage of delivered equipment cost method for estimating the total capital investment or total plant cost of a fast pyrolysis plant. This method usually used during the feasibility assessment of a project and is related to the cost of each process equipment. Another capital cost equation applied by Uslu (2005) in which a capital investment curve was developed based on five data points, eliminating a drying system. Furthermore, Brammer et al. (2005) calculated the investment cost for a pyrolysis (fluidised bed system) as a function of the willow mass input flow in kg per second. Finally all data have been joint to come to a final equation that can be used for preliminary plant cost estimations depending on the hourly amount of feedstock (Φ) that is converted:

$$I_{0,pyr} = 3.487 \text{ x } \Phi^{0,69} \tag{5}$$

With $I_{0,pyr}$ = investment expenditure in year 0 of the pyrolysis plant (MEUR);

Φ = hourly input flow of willow feedstock (ton dry matter per hour).

It can be derived from the exponent in Eq. 5 that economies of scale are assumed. When the processing capacity Φ doubles, the investment cost of the fast pyrolysis reactor increases only with a factor 1.6 (= $2^{0.69}$). The constant and the exponent of the investment expenditure equation however are uncertain: the constant is expected to fall between 2.697 and 4.286 with an expected value of 3.487 (see Eq. 5) and the value of the exponent is believed to be between 0.65 and 0.74 with an expected value of 0.69 (see Eq. 5) (Kuppens 2012). The capital cost of the CHP engine with de-NO_x-technology is estimated to be 600 EUR kW_e^{-1}. The total capital cost of the fast pyrolysis plant and the CHP engine is represented table 1. Capital costs are expressed in current prices by means of the Chemical Engineering Plant Cost Index (CEPCI).

[insert Table 1]

3.1.3 Operational costs

Fixed annual operational costs represent overheads, maintenance (labour and materials), insurance, etc. and are generally expressed as a percentage of the intial investment expenditure (Wright et al. 2010). Bridgwater et al. (2002) count a total of 4.5 % of the capital cost as fixed operational costs, whereas Islam and Ani (2000) count 8 % for fixed operational costs. Wright et al. (2010) count more or less 5.5 % of total capital investment for fixed operational costs. Besides, Magalhães et al. (2009) expect a maintenance cost of 3 % of total capital investment. Given these figures, total fixed operational costs in this case study are set at 5 % of the total plant cost, with a minimum of 3 % and a maximum of 8 %.

Other operational costs are the purchase cost of the biomass (which includes the cost of planting,and harvesting), transport costs, pretreatment costs, labor costs, the landfill cost of the char and water consumption. Calculations for the Campine region yield a cultivation and harvesting cost between 30 and 70 EUR t_{dm}^{-1} with a most probable value of 50 EUR t_{dm}^{-1} (Kuppens 2012). The 2,400 ha of farmland dedicated to phytoextraction is spread over a region with a surface of 494 km² (Schreurs et al. 2011), so that the average transportation distance of the willow equals 25 km round trip. The calculation of the transport cost of the willow biomass is based on the study of Voets et al. (2013) who built a transport cost model consisting of distance fixed and distance dependent transport costs assuming transport movements by means of a tractor-trailer. The expected transport cost according to this study is 7 EUR t_{dm}^{-1}.

Before willow can be pyrolyzed, it should be grinded into small particles of only a few mm and dried to a moisture content of ideally 7 % in order to avoid secondary reactions of the pyrolysis vapors (before condensation) with the formed char and aging of the pyrolysis oil respectively. Koppejan and de Boer-Meulman (2005) state that cutting the willow in small particles costs 10 EUR per fresh ton of willow. The pyrolysis gases provide the energy used in the drying process, which has been reported in Rogers and Brammer (2012) and Kuppens (2012), including the cost of a pilot fuel. Staffing levels have been based on Thornley et al. (2008) who calculated the potential for job creation based on several bioenergy systems. Wages are expected to be around 56.5 kEUR yr^{-1} in the sector of bioenergy production

(Kuppens 2012). Make-up water (the loss of cooling water through evaporation that should be replenished) consumed is based on a techno-economic evaluation of a bubbling fluidized bed pyrolysis unit and equals 0.1 tonne of water per tonne of feedstock at a cost of 0.77 EUR m^{-3} (Westerhout et al. 1998; Kuppens 2012). Finally, the total cost of landfilling industrial waste is set at 122 EUR per ton char (Kuppens et al. 2011).

3.1.4 Revenues

Revenues consist of the investment allowance subsidy, the sales and savings of electricity and heat, and the policy support in the form of sales of green power and heat and power certificates. Environment friendly investments receive an investment allowance of 13.5 % of the capital cost in Belgium. Electricity might be sold to the grid at prices between 60 and 80 EUR MWh_e^{-1} (Kuppens 2012), whereas heat savings are expected to be worth 20 EUR MWh_e^{-1} (De Paepe and Mertens 2007; Voets et al. 2011; Van Dael et al. 2013). In Flanders, green power certificates are awarded for electricity produced from renewable energy sources. The electricity producers can sell their certificates to electricity suppliers who are bound by the government to submit green power certificates for a minimal percentage of their total electricity supplies. The exact number of green power certificates awarded per MWh_e has depends on the profitability (indicated by the "unprofitable top" and "banding factor") for reference installations in several representative project categories. These indicators for the profitability of a biomass plant are recalculated yearly and might thus change over time after refinement the system of green power certificates. For new incineration installations of fixed biomass that become operational after 1st January 2017 this banding factor corresponds to 1, which in turn corresponds to 97 EUR MWh_e^{-1} per green power certificate. Therefore, it is assumed that pyrolysis of fixed biomass will also yield more or less 100 EUR MWh_e^{-1} per green power certificate, with a minimum of 80 EUR MWh_e^{-1} and a maximum of 120 EUR MWh_e^{-1} (Kuppens 2012). An analogous policy support system exists for the combined production of heat and electricity with heat and power certificates that are awarded for the amount of primary energy savings (PES). It is expected that the heat and power certificates will yield 31 EUR MWh_{PES}^{-1} and 45 EUR MWh_{PES}^{-1} with a most expected value of 35 EUR MWh_{PES}^{-1} (Kuppens 2012).

3.1.5 NPV

The cash flows generated by an investment of 10.7 MEUR for a fast pyrolysis plant that converts willow at 2.74 t_{dm} h^{-1} for the combined production of electricity and heat with a net electric capacity of 5.5 MW_e, result in a positive NPV over 20 years of 3.0 MEUR, i.e. for the base-case assumptions the investment in a fast pyrolysis plant for the valorization of phytoextracting crops appears to be profitable with an internal rate of return of 6 %. The expected cash flows for year 1 are reproduced in table 2.

The capital cost (which represents the annualized investment expenditure) is the most important expenditure with a share of 30 % of the total. The second most important is the purchase cost of the biomass with a share of 20 % of total expenditure. The variable cost of the CHP engine amounts up to 19 % of total expenditure. The transport costs are quite low, due to the fact that the biomass only needs to be delivered from a small local contaminated region. Other expenditure items each account for less than 10 % of total expenditure.

When revenues are considered, the green power certificates catch the eye: they make up 46 % of total revenues. If the systems of green power and heat and power certificates would be abolished, a total of 61 % of all revenues would be lost and result in bankruptcy for the pyrolysis plant.

3.1.6 Scale of operation

It has already been stated that economies of scale have been taken into account in the investment expenditure. Other economies of scale are present in fixed costs, the operational costs of the CHP and staff costs. The scale of operation greatly influences the profitability of an investment in a fast pyrolysis plant, as illustrated by figure 2 where the lines represent total revenues and the bars represent total costs. If only 650 ha of farmland would be remediated, then NPV would be slightly negative, i.e. -0.4 MEUR while in the base-case conversion of the biomass yield of 2,400 ha of farmland would result in a NPV of 3.0 MEUR which rises to 4.4 MEUR if 3,000 ha of farmland would be available.

[insert Fig. 2]

[insert Table 2]

3.2 Monte Carlo simulations

It is uncertain that the NPV of an investment in the fast pyrolysis plant will be 3.0 MEUR. 10,000 Monte Carlo simulations have been performed in order to check the sensitivity of the NPV for changes in the values of the input variables and in order to indicate the extent to which an investor runs the risk of a negative NPV. At first, 14 variables were allowed to change to the same extent (+ or – 10 %) and according to realistic ranges for the variables' values, but the NPV was not very sensitive to the fixed operational cost of the fast pyrolysis reactor, the price of the make-up water, the landfill cost per tonne of char, and the price of heat. As a consequence, only the values of the 10 variables stated in table 3 were allowed to change during Monte Carlo simulations within their indicated ranges.

[insert Table 3]

Under the above stipulated assumptions and uncertainties, there is a 87 % chance of a positive NPV. The mean NPV equals 3.2 MEUR which is close to the base-case NPV of 3.0 MEUR. The standard deviation equals 3.1 MEUR. A summary of the Monte Carlo statistics can be found in table 4.

[insert Table 4]

In figure 3 one can see the contribution of the uncertainty of each variable to the variance of the NPV. A positive percentage indicates that an increase in the value of a variable augments the NPV and hence increases the profitability of the investment. A negative contribution indicates that an increase in the value of a variable lowers the NPV of the investment. For example, if more farmland is available for phytoextraction, economies of scale come into play as was stated in paragraph 0 “

Scale of operation" and illustrated in figure 2. Here the presence of economies of scale is confirmed because of the positive relationship between available farmland and the NPV. The investment exponent (which equals 0.69 in Eq. 5) has a slightly negative influence on the NPV: a higher exponent increases the investment cost and hence lowers the NPV. A higher investment exponent also reflects less economies of scale. The most important variables influencing the NPV are: available farmland (i.e. the scale of operation), the willow biomass yield, the product yield (oil yield), the market prices of the green power certificates, the willow purchase cost and the electricity price. Together the uncertainty of the first four variables explains more than 70 % of the total variance in the NPV.

[insert Fig.3]

Finally, the numerical values for the input variables in the Monte Carlo simulations (drawn at random from their assumed probability distributions) are inserted into a meta-regression model. The coefficients of this model can be found in table 5. This model can now be used to estimate the NPV of a specific scenario. For example, if one wants to calculate the NPV for the base-case, just fill out the base-case values of table 3. The signs of the coefficients correspond to the signs of the contribution of each variable to the variance of the NPV illustrated in figure 3. All coefficients are statistically significantly different from zero at a 5 % significance level and the ranking of the variables according to their standardized coefficients corresponds to the ranking from Fig. 2.

[insert Table 5]

3.3 Plackett-Burman designs

The same uncertainties have been investigated by means of Plackett-Burman designs. For the 10 independent variables, 12 Plackett-Burman designs and 12 Box-Wilson foldover designs have been simulated. The results of the design are represented in table 7. In each run, an independent variable can take its base-case value (indicated by a plus sign) or its extreme value that has a negative impact on the dependent variable, i.e. the NPV (indicated by a minus sign). This corresponds to its minimal value (cf. table 3) if a lower value has a negative impact on the NPV as a dependent variable (e.g. a lower calorific value which decreases energy production and hence sales of electricity); it is the maximal value (cf. table 3) for independent variables that have a negative impact on the NPV (dependent variable) if an increase in their value impacts negatively on the NPV (e.g. the investment exponent). The Box-Wilson foldover is the opposite of the Plackett-Burman run: i.e. when the available farmland (independent variable) takes its base-case value in the first run of the Plackett-Burman design (as indicated by the plus sign in column 'PB1' in table 7), it will take a minus sign in the first run of the opposing Box-Wilson foldover. This means that in the 12th run of the Box-Wilson foldover every independent variable takes its base-case value, and hence the NPV (dependent variable) of this 12th run corresponds to the NPV of the base-case of 3.0 MEUR.

As explained in 2.3 every run (except the 12th Box-Wilson run) has half of the independent variables at their extreme value negatively impacting the dependent variable (NPV). Hence it is clear that all results are lower than the base-case result. The meta-regression model of these 24 runs is represented by table 6. The coefficients in this table should be interpreted somewhat differently compared to the ones from the Monte Carlo simulations in table 5. Here, if the independent variable y_{GPC} changes from -1 to +1, i.e. when the policy support system yields 100 EUR MWh_e^{-1} instead of 80 EUR MWh_e^{-1}, the NPV (dependent variable) will increase with 797 kEUR, i.e. the unstandardized coefficient of y_{GPC} in table 6. The unstandardized coefficient from the Monte Carlo simulations in table 5 is lower and cannot be compared because it is related to the independent variable x_{GPC} instead of y_{GPC}. It means that, when x_{GPC} increases with 1, in other words when the policy support scheme yields 1 EUR MWh_e^{-1} extra, the NPV (dependent variable) augments with 154 kEUR, i.e. the unstandardized coefficient of x_{GPC} in table 5.

The first thing to note is that none of the coefficients is significant at the 0.01 level. Only 3 coefficients are significant at the 0.05 level: the coefficients linked to the independent variables (i) available farmland, (ii) sales price of the green power certificates and (iii) oil yield. It is striking that the sign of the estimator of the main effect of the available farmland does not correspond to the sign reflected by one-factor-at-a-time sensitivity analysis or to the sign this independent variable has in table 5. This can be explained by the huge difference in available farmland that the -1 value represents compared to the +1 value: when the independent variable y_{ha} equals -1 it actually represents a case where the minimal farmland is 650 ha, compared to 2,400 ha when y_{ha} equals +1. When there is only 650 ha of farmland available, the scale of the plant might be too low in order to be realistic and hence the effect of the available farmland might not be representative for realistic cases. Comparing table 5 and 6, one can see also differences in the signs of the coefficients for the independent variables (i) willow purchase cost, (ii) investment constant and (iii) investment exponent. The difference in sign can be expected, as the Plackett-Burman simulations measure the effect of changing the independent variable y_{wilpur} from -1 to +1, i.e. from the extreme value negatively impacting the NPV (or the maximal value of 70 EUR t_{dm}^{-1} in table 3) to the base-case value of 50 EUR t_{dm}^{-1}. The NPV (dependent variable) should be higher if y_{wilpur} (independent variable) equals +1 compared to -1, and that corresponds to the positive sign of the standardized coefficient of 0.303 in table 6. This appears to contrast with the negative sign of the standardized coefficient of -0.299 in table 5 but it is not: the effect of the unit willow purchase cost is measured differently during Monte Carlo simulations by means of the independent variable x_{wilpur}. In the base-case x_{wilpur} takes the value of 50 EUR t_{dm}^{-1}: when the purchase cost increases, i.e. when x_{wilpur} augments, this higher purchase cost results in a lower NPV as indicated by the minus sign of -0.299 in table 5. Although the signs differ in both tables, it (counter-intuitively) represents the same effect. Finally, one can see that the standardized coefficients in table 6 have the same order of magnitude compared to the ones in table 5 (except the standardized coefficient of the willow yield).

[insert Table 6]

[insert Table 7]

4. Conclusion and Discussion

The base-case economic model indicated that the NPV of an investment in fast pyrolysis is positive, which means that the revenues are high enough to recuperate the production cost of 180.96 EUR MWh^{-1} of electricity (= the total yearly expenditure of 5,545,241 EUR – see table 2 - divided by the product of the gross electric capacity of 5.5 MW_e and the 5,000 operation hours of the CHP engine). The base-case values however are highly uncertain. First, these uncertainties have been studied by Monte Carlo simulations. Under current knowledge, there is a 87 % chance of a positive NPV. The problem with Monte Carlo simulations is that the assumed probability distributions are often unknown and hence represent the best guess of the expert. Therefore, it has been argued that the results of Monte Carlo simulations might have a level of uncertainty, because the assumed distributions might differ from reality.

The Plackett-Burman design and its Box-Wilson foldover are suggested as an alternative for estimating risk. The problem with the Plackett-Burman design is that they are more difficult to interpret: as the variables either take a value of +1 or -1, the estimator of the main effect is not comparable to the estimator found during Monte Carlo simulations. The standardized coefficients however have more or less the same magnitude, but are often not significant. Another problem is that the Plackett-Burman technique only focuses on the extreme values of the ranges found in literature. Whereas in Monte Carlo simulations a random selection of variable values is applied, Plackett-Burman designs result in non-random scenarios. The result of this may be that some factors are over- or underemphasized for decision making (Van Groenendaal and Kleijnen 2002), although information on the extremes is valuable for decision makers. It is suggested that both Monte Carlo and Plackett-Burman simulations provide complementary information for decision makers. The focus for the Plackett-Burman design should not be on the meta-model, but on the possible outcomes of the NPV: they indicate the maximal losses an investor can run. It is believed that for the main effects the meta-model of the Monte Carlo simulations is better suited.

In our opinion, design of experiments is helpful to gain a first understanding of the problem and does not fully grasp economic risk as these techniques are only concerned with the worst case values of the input variables of the techno-economic model. There are two important drawbacks: only two values are being used for each variable, where they could, in fact, take any number of values; and no recognition is being given to the fact that the base-case value is much more likely to occur than the extreme values having a negative impact on the NPV.

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Table 1 Total capital cost of the fast pyrolysis plant

Processing capacity	2.74 t_{dm} h^{-1}
Gross electric power	5.5 MW_e
Capital cost pyrolysis reactor	7.0 MEUR
Capital cost CHP engine	3.7 MEUR
Total plant cost	10.7 MEUR

Table 2 Expected cash flows for a fast pyrolysis plant in the Belgian Campine converting 2.74 t_{dm} h^{-1} in year 1

Expenditure/revenue item	Amount (EUR)	Share of total expenditure/revenue (%)
Total expenditure	**4,818,725**	**100 %**
Capital cost	1,345,311	28 %
Fixed costs pyrolysis	350,221	7 %
Variable cost CHP	891,698	19 %
Biomass purchase cost	960,000	20 %
Biomass transport cost	134,400	3 %
Biomass pretreatment cost	192,000	4 %
Staff cost	282,500	6 %
Char landfill cost	289,837	6 %
Water consumption	1,478	0 %
Pilot fuel	371,280	8 %
Total revenues	**5,545,241**	**100 %**
Electricity sales	1,863,963	34 %
Heat sales	214,737	4 %
Green power certificates	2,534,133	46 %
Heat and power certificates	932,408	15 %

Table 3 Uncertainty ranges for Monte Carlo simulations

Variable	Symbol	Values		
		Minimal	Base-case	Maximal
Available farmland	x_{ha}	650 ha	2,400 ha	3,000 ha
Willow yield	x_{tdm}	5 t_{dm} ha^{-1} yr^{-1}	8 t_{dm} ha^{-1} yr^{-1}	15 t_{dm} ha^{-1} yr^{-1}
Oil yield	$x_{oil\%}$	60 %	65 %	70 %
Sales price green power certificates	x_{GPC}	80 EUR MWh_e^{-1}	100 EUR MWh_e^{-1}	120 EUR MWh_e^{-1}
Sales price heat and power certificates	x_{HPC}	31 EUR MWh_{PEB}^{-1}	35 EUR MWh_{PEB}^{-1}	45 EUR MWh_{PEB}^{-1}
Sales of electricity	x_{elec}	60 EUR MWh_e^{-1}	70 EUR MWh_e^{-1}	80 EUR MWh_e^{-1}
Willow purchase cost	x_{wilpur}	30 EUR t_{dm}^{-1}	50 EUR t_{dm}^{-1}	70 EUR t_{dm}^{-1}
LHV of pyrolysis oil	x_{LHV}	16 GJ t^{-1}	17 GJ t^{-1}	18 GJ t^{-1}
Investment constant	x_{cst}	2.697	3.487	4.286
Investment exponent	x_{exp}	0.6267	0.6914	0.7799

Table 4 Summary statistics of the Monte Carlo simulations

Statistic	Forecast values
Trials	10,000
Base-case	3.0 MEUR
Mean	3.2 MEUR
Standard Deviation	3.1 MEUR
Minimum	-3.8 MEUR
Median	2.7 MEUR
Maximum	20.8 MEUR

Table 5 Coefficients of the regression analysis based on the Monte Carlo simulations

Variable	Symbol	Unstandardized coefficient	Standardized coefficient
(Constant)		-77,793,759.83	
Available farmland	x_{ha}	2,911.15	0.460***
Willow purchase cost	x_{wilpur}	-114,346.07	-0.229***
Investment constant	x_{cst}	-2.21	-0.228***
Investment exponent	x_{exp}	-7,608,214.81	-0.076***
LHV of pyrolysis oil	x_{LHV}	1,299.43	0.171***
Sales of electricity	x_{elec}	156,955.56	0.205***
Sales price of green power certificates	x_{GPC}	153,622.95	0.403***
Sales price of heat and power certificates	x_{HPC}	141,866.01	0.133***
Willow yield	x_{tdm}	640,138.27	0.425***
Oil yield	$x_{oil\%}$	52,617,305.83	0.347***

Table 6 Coefficients of the regression analysis based on the Plackett-Burman and Box-Wilson simulations

Variable	Symbol	Unstandardized coefficient	Standardized coefficient
(Constant)		-2,776,261.83	
Available farmland	y_{ha}	-869,991.40	-0.420*
Willow purchase cost	y_{wilpur}	627,176.98	0.303
Investment constant	y_{cst}	546,064.11	0.264
Investment exponent	y_{exp}	59,127.00	0.029
LHV of pyrolysis oil	y_{LHV}	317,356.80	0.153
Sales of electricity	y_{elec}	467,979.00	0.226
Sales price green power certificates	y_{GPC}	797,135.41	0.385*
Sales price heat and power certificates	y_{HPC}	230,059.96	0.111
Willow yield	y_{tdm}	-318,238.37	-0.154
Oil yield	$y_{oil\%}$	696,530.53	0.337*

Table 7 Results of the Plackett-Burman design and Box-Wilson foldover

Variable	Symbol	PB1	PB2	PB3	PB4	PB5	PB6	PB7	PB8	PB9	PB10	PB11	PB12
Available farmland	y_{ha}	+	+	-	+	+	+	-	-	-	+	-	-
Willow purchase cost	y_{wilpur}	-	+	+	-	+	+	+	-	-	-	+	-
Investment constant	y_{cst}	+	-	+	+	-	+	+	+	-	-	-	-
Investment exponent	y_{exp}	-	+	-	+	+	-	+	+	+	-	-	-
LHV of pyrolysis oil	y_{LHV}	-	-	+	-	+	+	-	+	+	+	-	-
Sales of electricity	y_{elec}	-	-	-	+	-	+	+	-	+	+	+	-
Sales price green power certificates	y_{GPC}	+	-	-	-	+	-	+	+	-	+	+	-
Sales price heat and power certificates	y_{HPC}	+	+	-	-	-	+	-	+	+	-	+	-
Willow yield	y_{tdm}	+	+	+	-	-	-	+	-	+	+	-	-
Oil yield	$y_{oil\%}$	-	+	+	+	-	-	-	+	-	+	+	-
NPV Plackett-Burman run (MEUR)		-5.3	-4.6	-1.8	-3.5	-3.3	-2.8	-1.7	-1.5	-3.3	-2.5	-0.7	-2.3

NPV Box-Wilson foldover (MEUR)	-2.0	-1.0	-4.3	-2.2	-2.1	-2.7	-5.0	-6.7	-1.7	-1.5	-7.0	+3.0

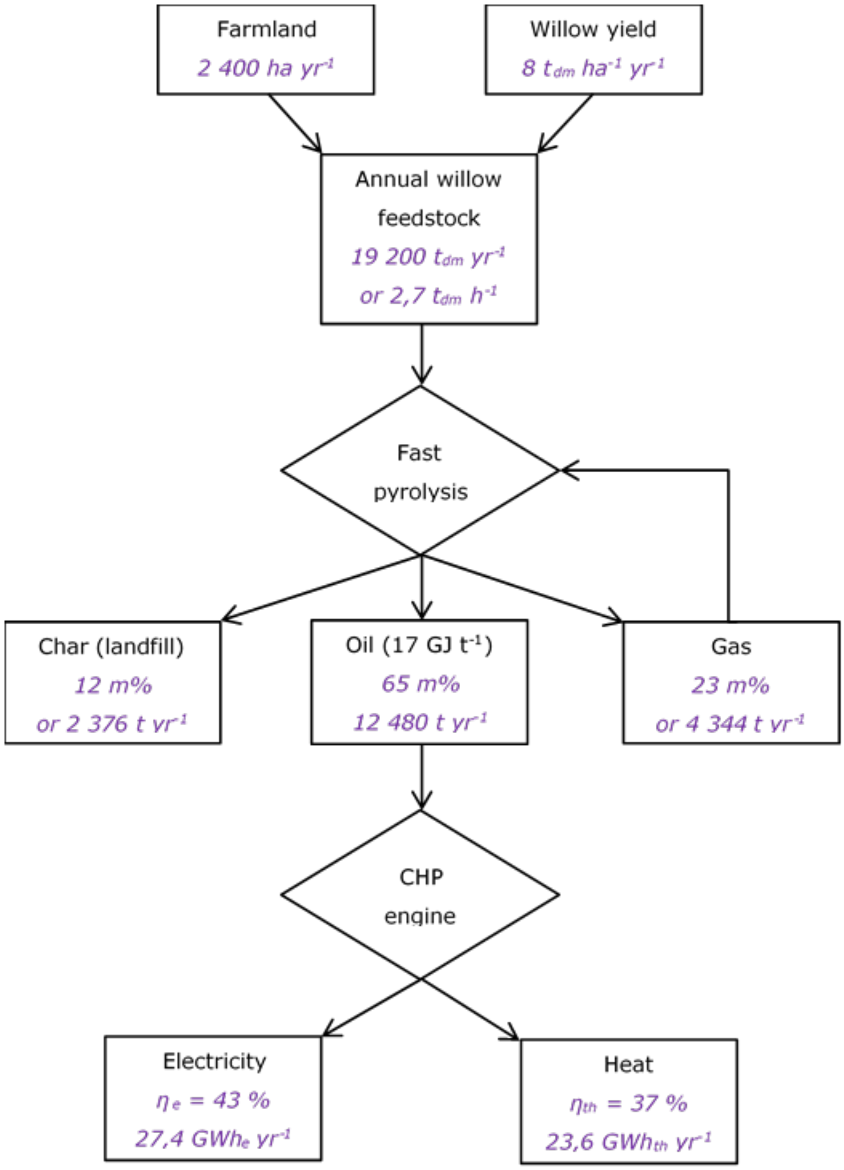

Fig. 1 Simplified mass and energy balance of the fast pyrolysis case study

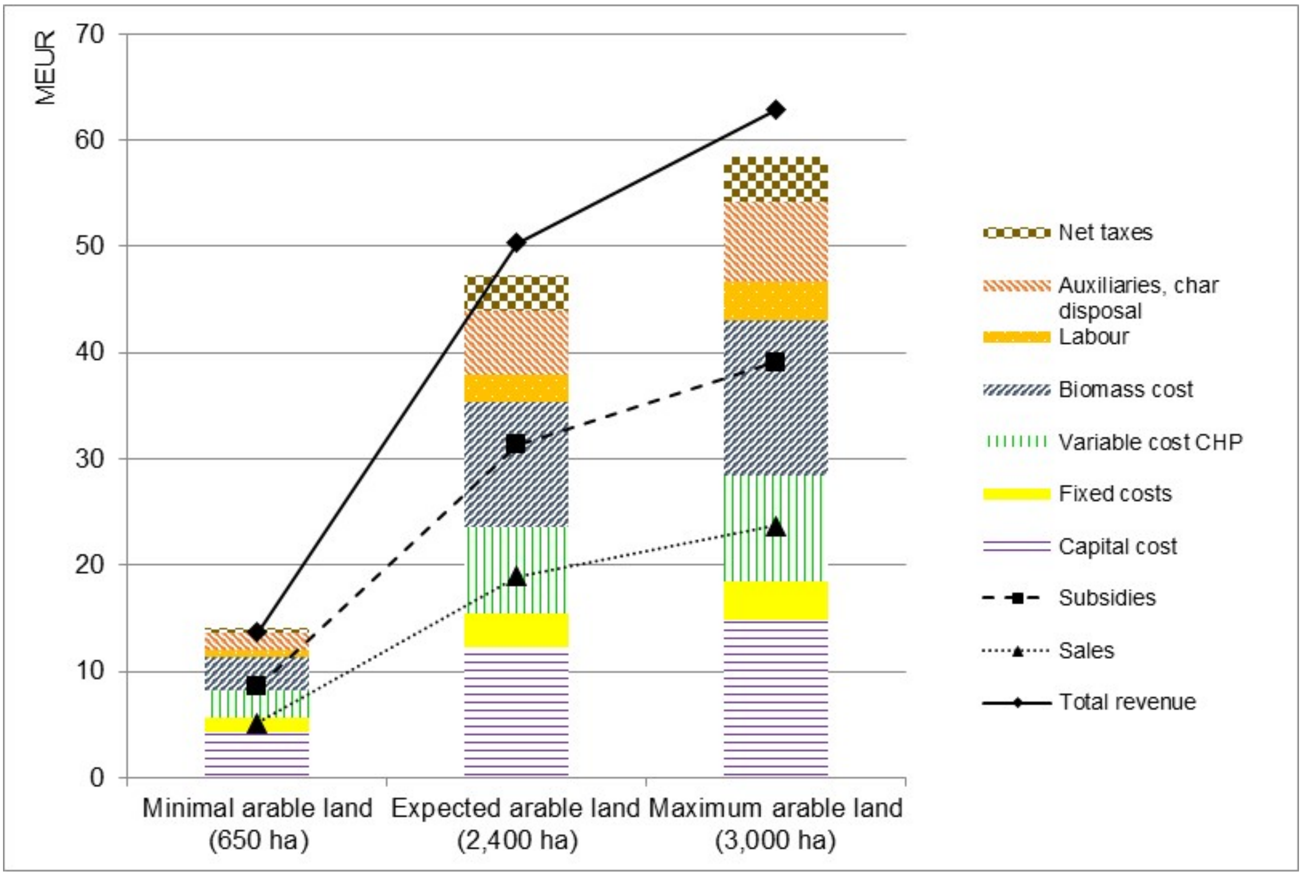

Fig. 2 Influence of scale on total capital cost, operational costs and revenues

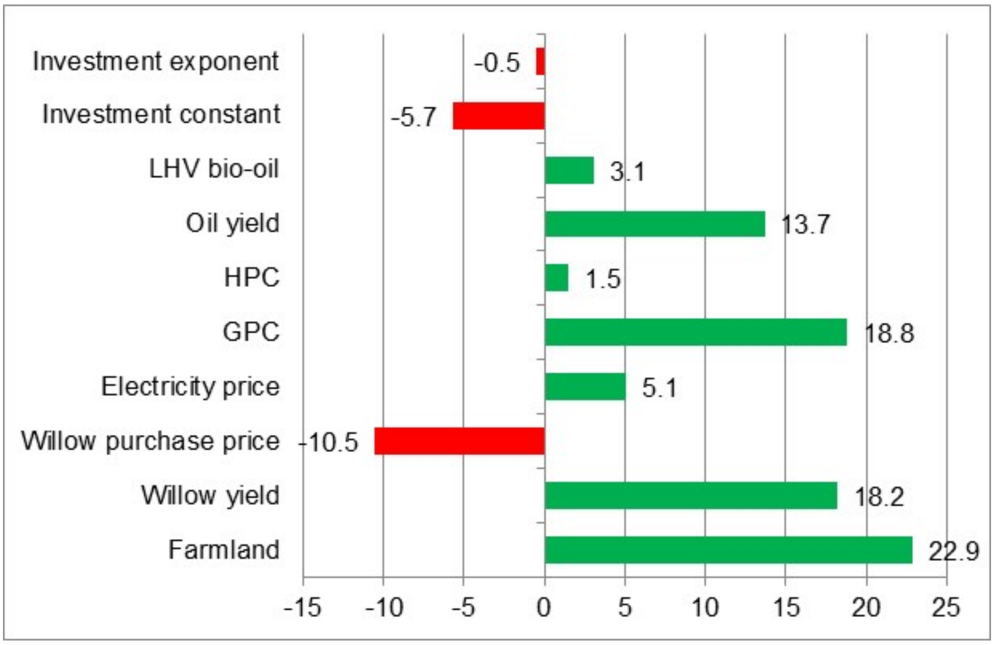

Fig. 3 Sensitivity analysis – contribution to variance of the NPV