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Abstract

There are two prominent approaches in the valuation of American option, if no closed-form solution is available: stochastic simulation based on binomial (trinomial) scenario tree, and Monte-Carlo simulation. Yet, in practice real options rarely stand alone; and neither method excels in the valuation of compound American option subject to resource endowments and returns-to-scale, as well as a set of investment options of predefined sizes. In this paper, we develop an approach, based on Monte-Carlo simulation, scenario tree reduction, and stochastic programming. It is especially advantageous for real options valuation where not only timing, but also the scale and interaction with constraints and alternative activities matter. For illustrative purposes, we employ the option to adopt, harvest, and reconvert perennial energy crop in a farm-level context.

Keywords: Scenario Tree Reduction, Compound Option, American Option, Farming Investment Decision, Bioenergy.
JEL classification: C61, C63, G32, Q12, Q42

1 Introduction

In the absence of a closed-form solution, real options are valued with numerical methods. In case of simple European options, this is often done by the Black-Scholes-Merton model (Merton 1973). As for American options, there are two prominent approaches: stochastic simulation based on binomial (trinomial) scenario tree (e.g. Cox, Ross, and Rubinstein 1979; Trigeorgis 1991), and Monte-Carlo simulation (Boyle 1977), including computationally more efficient Least Squares Monte-Carlo (LSMC) Simulation Method (Longstaff and Schwartz 2001). A binomial (trinomial) scenario tree is an intuitive and generic approach, however, it suffers from the curse of dimensionality and leads to branches with exploding values or values close to zero already under rather conservative assumptions about the variance at nodes (Lander and Pinches 1998, pp.545–546). That limits its applicability to compound options and over a long time horizon. The LSMC method efficiently deals with compound options, but is often criticized for being sensitive to the choice of functional form in the regression step (e.g. Stentoft 2004, p.136), especially if the dimension increases (Bouchard and Warin 2012, p.216).

Characteristics of large real-world investment projects often do not fit well to the restrictions explicitly or implicitly inherent in existing numerical valuation methods for real options. In this paper, we focus on investment projects that involve compound American real options and/or compete with other activities for (quasi-)scarce resources. In addition, returns-to-scale or investment options of predefined sizes can be involved. Examples include investment in indivisible assets, investment characterized by a high share of transaction or other (quasi-) fixed costs, as well as investment of (quasi-)scarce resources with competing uses. In order to advance in capturing the complexity of such large investment projects, we develop an alternative numerical method that combines and benefits from the scenario tree and the Monte-Carlo simulation methods.

In this study, we suggest applying a scenario tree reduction technique to the outcome of a Monte-Carlo simulation. We hence control for dimensionality and obtain an advanced scenario tree that enters stochastic programming which values the real options. In contrast to the Least Squares Monte-Carlo, we don’t approximate the fitted payoffs and hence the optimal investment decision by one function; instead we consider the fragmented distribution of self-contained expected payoffs. In order to illustrate our approach and show its applicability to a complex real-world example, we chose a case study from agricultural economics, namely investment analysis of perennial energy crops cultivation. That seems especially interesting as the real options theory has gained interest in analysis of agricultural investment projects (e.g. Wossink and Gardebroek 2006; Hinrichs, Mußhoff, and Odening 2008; Hill 2010), but empirical applications are so far rather limited. Our example depicts a case where not only timing, but also the scale of the investment and its interaction with alternative activities matter due to competition for the endowments.

The remainder of this paper is organized as follows. Section 2 provides methodological background of option valuation and identifies the gaps addressed in the paper. Section 3 introduces the general methodology proposed. Section 4 illustrates our approach for the chosen case study. Section 5 presents core empirical findings of the case study to exemplify the type of results which the methodology provides. Section 6 comments on further application fields for the proposed approach before section 7 concludes.

2 State of the art

Lander and Pinches (1998) distinguish the main reasons why practitioners are reluctant to employ the real options for investment analysis. First, the existing models and methods of real options valuation can be deemed obscure and hard to follow; second, often restrictive assumptions are required in order to be able to solve the model. Below we address those two issues while summarizing the major existing methods of real options valuations.

Analytical solutions for real options valuation (e.g. Black and Scholes 1973; Geske and Johnson 1984) are elegant from a scholarly perspective, but often deemed inappropriate due to restrictive assumptions required, e.g. about stochastic processes. If that is the case, a numerical method has to be employed instead (Trigeorgis 1996; Regan et al. 2015). Cetinkaya and Thiele (2014, p.12) distinguish here between methods approximating the underlying stochastic process and methods approximating the partial differential equations (see e.g. Trigeorgis (1996) for an overview of the latter). The most well-known method that approximates the partial differential equations - the Black-Scholes-Merton model (Merton 1973) - was initially designed and is well suited for valuation of simple European options (Regan et al. 2015, p.146). In contrast, compound American options are typically valued by approximating stochastic process methods. They can be further divided into Monte-Carlo simulation (Boyle 1977), including computationally more efficient the Least Squares Monte-Carlo method (Longstaff and Schwartz 2001), and scenario tree approximation.

The scenario tree approximation method usually implies either a binomial lattice or a binomial scenario tree (Brandão and Dyer, 2005; Smith, 2005). An (approximate) optimal value for option(s) depicted by the constructed scenario tree or lattice is than found by dynamic programming (e.g. Dixit and Pindyck 1994, pp.140–147; Guthrie 2009, pp.88–92). Programming approaches are widely used to analyse investment decisions in a quantitative and relatively transparent way, including applications of stochastic programming (e.g. Brandes, Budde, and Sperling 1980; Haigh and Holt 2002). Examples of real options valuation with stochastic programming include, among others, energy economics (Sagastizábal 2012; Feng and Ryan 2013; Simoglou et al. 2014; van Ackooij and Sagastizábal 2014), managing project portfolio (Beraldi et al. 2013), and natural resources extraction (Alonso-Ayuso et al. 2014). One of the main disadvantages of a scenario tree approximation is that a tree can quickly become unsolvable in terms of computational capacity, as the number of time periods increases (Lander and Pinches 1998, pp.545–546), since a binomial lattice requires $[(n(n+1))/2]$, and a binomial tree - 2^n final leaves for n time periods. Furthermore, developments of stochastic parameters in a binomial tree with chained relative ups and downs in each node can lead after a few time points to unrealistic values, since already rather conservative assumptions about the variance at any node can imply exploding branches.

The alternative Least Squares Monte-Carlo (LSMC) method evolves from the core finding that the optimal strategy is determined by the conditional expectations of the value to postpone exercising the option; and these conditional expectations can be estimated using the results of a simulation (Longstaff and Schwartz 2001, p.114). Thus, the method consists of the following three steps: (i) simulation of the payoffs in every time period if exercising the option now and keeping it in the previous periods; (ii) regression of those payoffs using least squares; and (iii) specification of the optimal strategy based on the estimated regression and fitted payoffs. The method is considered as highly powerful to value American options and widely used in the literature (see e.g. Sabour and Poulin 2006; Abadie and Chamorro 2009; Zhu and Fan 2011). A disadvantage discussed with respect to the LSMC method refers to a functional form that must be assumed for the estimation of the Lagrangian and can be crucial for determining the optimal strategy (e.g. Stentoft 2004, p.136). Although follow-up papers addressed that issue, including Rogers (2002), Haugh and Kogan (2004), and Létourneau and Stentoft (2014), there is still no general payoff independent choice algorithm which also works for higher dimensional problems (Bouchard and Warin 2012, p.216).

Accordingly, there is room for alternative methods, especially when they are able to relax otherwise required restrictive assumptions which motivates our approach.

Another reason identified by Lander and Pinches (1998) why the real option theory is not applied is that existing valuation methods fail to capture the complexity of real-world investment projects. In the following, we focus on large investment projects that typically not only involve compound real options, but also compete for (quasi-)scarce resources. It implies that (changes in) the returns to inputs and possible adjustment in management resulting from re-allocating these resources need to be considered as well. This interaction between endowment constraints and alternative activities is especially crucial in the context of returns-to-scale and/or a set of investment options of predefined sizes (i.e. binary decision variables). In such cases, both timing and scale of exercising an option are at issue. Examples include investment in indivisible assets, investment characterized by a high share of transaction or other (quasi-)fixed costs, as well as investment impacting the competing use of resources. All methods discussed above are for different reasons not well suited for these problem settings. The Black-Scholes-Merton model is not appropriate for valuing compound American options. Due to the curse of dimensionality, a binomial scenario tree hampers valuation of compound options, in particular over a long time horizon. The LSMC method impedes the choice of Lagrangian function under high dimension. In addition, the LSMC requires solving a programming model for each single fitted payoff, if interaction with constraints and alternative activities is considered, which threatens its computational efficiency. We therefore discuss our alternative approach which is particularly relevant if alternative activities, returns-to-scale, indivisible assets, as well as resources’ endowments and other constraints are jointly considered.

For illustrative purposes we employ a case study relating to an agricultural investment project that is characterized by limited resources, returns-to-scale, and predefined sizes of available investment options. Our example refers to farm-level decision to adopt, harvest and reconvert a perennial energy crop in the context of farm constraints and alternative activities. The application of the real options in agricultural economics is rather limited, especially in terms of investment analysis of perennial energy crops adoption; the dominant approach in the literature is the classical net present value (e.g. Lothner, Hoganson, and Rubin 1986; Strauss et al. 1988; Gandorfer, Eckstein, and Hoffmann 2011; Schweier and Becker 2013). The few existing models based on the real options either considered perennial energy crops cultivation as standing alone investment option (Frey et al. 2013), or (partly) killed managerial flexibility it allows for (Bartolini and Viaggi 2012), or both (Song, Zhao, and Swinton 2011; Musshoff 2012; Wolbert-Haverkamp and Musshoff 2014). These restrictive assumptions were made, in order to gain tractability and computational efficiency, as discussed previously.

The objective of the paper is twofold. First, we aim to develop an alternative approach that allows for a straightforward valuation of compound American options in the context of returns-to-scale, resources’ endowments and binary decision variables. Second, we fill the gap in limited application of the real options in agricultural economics by designing and valuating a farm-level model of perennial energy crops adoption, in order to illustrate our approach.

3 General methodology

The approach we propose can be summarized in four main steps. *First*, we define the (state contingent) decision variables of the problem and the available (compound) real options. *Second*, we define the relations (i.e. equations and constraints) between these decision variables, including lagged relations between time points, and combine them into a programming model. Simultaneously, we also introduce node indices for the state contingent decision variables while reflecting the ancestor relation between lagged nodes (states). The first two steps hence design a deterministic mixed-integer linear programming model. Integers, including binaries, enable to differentiate between investment options of predefined sizes; non-linearity allows reflecting returns-to-scale. On this step we also define the payoff function, e.g. net present value, subject to constraints, including resources' endowments. *Third*, having sketched a deterministic version of the programming model, we introduce different future outcomes (states) and related state contingent decision variables. In particular, we choose a distribution for the uncertain parameter(s), draw Monte-Carlo scenarios and construct from them a reduced scenario tree with probabilities, employing a scenario tree reduction technique. In order to convert the deterministic version into a stochastic programming equivalent, four additional elements are needed: (i) the decision variables need to carry an additional index for the decision node (i.e. state); (ii) an ancestor matrix, reflecting the order of the nodes in the decision tree, has to be introduced; (iii) outcomes for the stochastic parameters for each state need to be defined; and (iv) the probabilities for each node should be assigned. *Finally*, we employ stochastic programming to value the real options.

The third step is worth additional comments; therefore we will next discuss how the outcomes and related probabilities can be constructed. Here, we first assume distributions for the stochastic components and run Monte-Carlo simulations which result in a large-scale scenario tree that is numerically not solvable due to the curse of dimensionality. We hence aim at reducing the size of the tree without losing too much information about the underlying distributions, for which we employ the tree reduction and construction algorithm by Heitsch and Römisch (2008). Similar to a Gaussian quadrature, which describes a probability density function with a few characteristic values and their probability mass, this algorithm picks representative nodes and assigns probabilities to them to capture approximately the distribution in original trees[1]. The algorithm can be depicted graphically as lumping together neighbouring nodes and branches in the tree to bigger ones, where the thickness represents probability mass. In particular, we opt to use a pre-defined number of final leaves, and hence pre-determine the model's number of equations and variables, and let the algorithm decide which nodes to maintain. There is no well-established approach to determine the optimal number of leaves. The choice however should reflect a trade-off between accuracy and solution time: more leaves improve the results, while increasing the solving time substantially (Dupačová, Consigli, and Wallace 2000, p.30). The extreme case of small number of leaves is the classical net present value approach with one leaf only and no incentive to postpone. Adding one single leaf converts the problem into the real options and might create incentives to wait. Also note that the number of leaves has different influence on different outcomes of the model. In particular, it might be very hard to stabilize integer variables within a certain range of accuracy. We suggest here to proceed as follows: (1) choose the "main result variable" of the model; (2) decide on an appropriate degree of deviation for this variable; (3) run a sensitivity analysis with increasing number of leaves and check

[1] Basically all the methods of generating a scenario tree can be summarized as aggregating nodes and stages, trimming or refining the trees (see e.g. Klaassen 1998; Consigli and Dempster 1998; Frauendorfer and Marohn 1998; Dempster and Thompson 1999; Dempster 2006). A practical advantage of the method developed by Heitsch and Römisch (2008) is a GAMS tool SCENRED2 written on its basis.

this variable; and (4) stop increasing the tree size once the variable is stabilized within the deviation level.

Our approach allows assuming any risk attitudes. However, deviating from risk neutrality and using a risk-adjusted discount rate requires re-adjusting the discount rate for every time period, as the risk decreases when approaching the final leaves of the scenario tree (Brandão and Dyer 2005). In addition, different risk-adjusted discount rates should be applied to various risky farm activities (see e.g. Finger 2016).

We solve the model described above by stochastic programming using the following software: standard Java libraries[2] for Monte-Carlo draws, GAMS 24.3, a tree construction tool SCENRED2 (GAMS Development Corporation 2015), and an optimization solver CPLEX (IBM Corporation 2016). The computational speed can be increased by employing a multi-core processor. Also, the literature provides further techniques to gain computational efficiency for such large-scale mixed integer stochastic problems (see e.g. Escudero et al. 2012).

4 Empirical application

For illustrative purposes we value an investment decision in perennial energy crop, namely short-rotation coppice (SRC), which involves decision on timing and scale of adoption, harvesting and reconversion. That case study features the complexities discussed above: it constitutes a compound American option of predefined sizes in the context of limited resources, returns-to-scale, and alternative activities. We next present briefly the background for our case study, while Table 1 briefly summarizes the main characteristics considered in our example.

[2] The use of Java is mostly motivated by the fact that we store the generated draws along with the ancestor matrix describe the node structure efficiently in the proprietary data format GDX of GAMS to avoid costly computations in GAMS.

SRC uses fast growing trees that are harvested in relatively short intervals – typically between two and five years – to produce biomass for energy purpose. A SRC plantation is not clear-cut and can be harvested several times during its lifetime of up to 20 years. A large share of the costs is sunk, once the plantation is set-up: typically, about 2/3 of the costs of a SRC plantation relate to its planting and final re-conversion (Lowthe-Thomas, Slater, and Randerson 2010). SRC is characterized by low-input production comparing with alternative crops (Faasch and Patenaude 2012); planting and harvesting are usually outsourced to a contractor, such that little or no on-farm labour is required (Musshoff 2012, p.77). Land use competition between SRC and other crops has been reduced under the latest Common Agricultural Policy reform, which requires that large arable farms devote 5% of their farmland to “Ecological Focus Area” (EFA), for which SRC is to a certain degree eligible[3] (in Germany with a factor of 0.3 (Bundesministerium fuer Ernaehrung und Landwirtschaft 2015)).

During the lifetime of a plantation, farmers face (at least) uncertain prices for the harvested biomass. While the same might be said with regard to future returns for competing annual crops, the possibility to adjust the crop mix and cropping intensity on an annual basis might substantially reduce the subjective risk assessed by farmers being used to manage these crops (Di Falco and Perrings 2003). We define switching to SRC as a compound American option, where planting, each intermediate harvesting, and the final reconversion are the option stages. Due to stage contingent harvesting periods between two and five years and the maximum lifetime of a plantation, the number of total stages is not predetermined, but flexible. As a consequence, the sooner each stage is exercised, the more stages in total are available.

[3] We consider two options to meet the EFA requirements in our model: set-aside land (i.e. fallow land) and SRC (for other options, see Bundesministerium fuer Ernaehrung und Landwirtschaft 2015).

The data for the model are taken from Musshoff (2012); Faasch and Patenaude (2012); Wolbert-Haverkamp (2012) (see Appendix 1 for data used), and refer to cultivation of SRC poplar on a farm in the region Mecklenburg-Western Pomerania (northern Germany). The region is characterized, in comparison to average German conditions, by low soil quality and precipitation, and thus generates low returns from annual crops. That renders so far uncommon alternative land use options, in particular SRC, potentially attractive; in addition, according to Schuler et al. (2014, p.69), more than 90% of agricultural lands in this region are suitable for SRC cultivation.

In order to model the competition for farm resources, such as land and labour, we consider two alternative crops that are relevant for the case study region - winter wheat and winter rapeseed - of which the former is more labour intensive and has also a higher gross margin per hectare. Finally, we consider the EFA requirements and thus introduce set-aside as an alternative to SRC in order to fulfil these requirements.

We consider pre-defined plantation sizes, because farmers would typically convert existing plots into a SRC plantation. In particular, against a background of 100 ha total land endowment, we assume three plots[4] to be potentially converted to SRC – of 10 ha, 20 ha, and 40 ha, - providing eight possible combinations of total plantation sizes from 0 to 70 ha. Each plot is characterized by three core decision variables over the simulation horizon: (1) land use decisions: whether a plot is used for SRC or one of the three alternative activities; (2) SRC harvesting decisions, in case the plot is used for SRC: whether the plot is harvested in the current year or not; and (3) SRC reconversion decision, in case the plot is used for SRC and

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[4] Initially four plots and 11 combinations from 0 to 100 ha were assumed, covering hence all the available land area. Since tests revealed the optimal total area under SRC to be always below 40 ha, we restrict ourselves to three plots, as described in the text, in order to additionally decrease the number of variables and hence gain computational efficiency.

harvested in the current year[5]: whether the plot is converted back to traditional agriculture or not.

Revenues for a plot under SRC are linked to harvest decisions which are based on the interplay between functions depicting biomass growth and harvesting costs. Biomass growth is represented by a linear function of available yields and – combined with the harvesting decision in the previous year – provides the current yields. The harvesting costs function considers transaction costs for labour outsourcing, transport costs to the field, harvesting costs, costs for after-harvest fertilization, and costs for drying and storing the harvested biomass. In order to capture economies of scale in harvesting, we distinguish costs (a) at farm (fixed); (b) per plot (quasi-fixed); and (c) per ton of harvested biomass (variable) as follows:

$$HC = 66.75 + 272.13 * L + 10.67 * L * Y \qquad (1)$$

where
HC – total harvesting costs (i.e. all the costs related to harvesting), €;
L – area of land harvested, ha;
Y – yields harvested[6], t DM.

Considering different harvest intervals allows the plantation to function as storage for biomass, such that temporal arbitrage can be applied: one might let the trees grow if prices are currently low and expected to increase again. Moreover, since we specify fixed and quasi-fixed harvesting costs, the total harvesting costs per ton of dry matter yields decline the longer the plantation has grown since planting or the latest harvest; here, between two and five years are considered.

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[5] Reconversion can be exercised only in combination with harvesting. Costs for reconversion include harvesting costs and clear-cut costs.

[6] Hereinafter "DM" stays for "dry matter".

Table 1. Summary of the main characteristics of our case study.

Characteristics of a large real-world investment project	*Expressed in our case-study via*
Compound American option	Short rotation coppice plantation with initial planting (can be postponed by 3 yrs), intermediate harvestings (after 2-5 yrs from the previous stage, i.e. planting or harvesting), and final reconversion (after max. 20 yrs after planting, exercised only together with harvesting).
Stochastic component	Biomass price, i.e. price for short rotation coppice output.
Sunk costs	Planting costs, as well as costs associated with harvesting and final reconversion.
Predefined investment sizes	Predefined land plots to be potentially converted to short rotation coppice plantation.
Opportunity costs	Annual agriculture, in particular two types of annual agriculture, characterized by different inputs, i.e. land and labor, and output, i.e. gross margins.
Returns-to-scale	Costs associated with harvesting, which include costs (a) at farm (fixed); (b) per plot (quasi-fixed); and (c) per ton of harvested biomass (variable).
Resources' endowments	Land and labor; both assumed to be limited with no possibility to expand.
Policy constraints	"Ecological Focus Area": 5% of land endowment must be devoted to fallow land; alternatively, short rotation coppice plantation is recognized as fallow land with the coefficient 0.3.

Source: Own representation.

After setting up the mixed integer programming model[7] that maximizes the net present value the risk is introduced into the model. We assume the natural logarithm of the output price for SRC to follow a mean-reverting process (MRP), in particular an Ornstein-Uhlenbeck process (Musshoff 2012; de Oliveira et al. 2014). Having run Monte-Carlo simulation for the output prices with 10’000 draws, we apply a scenario tree reduction technique. In order to determine the optimal number of leaves, we chose the expected area under SRC as the main result, and stabilized it within +/-10% of the expected area under SRC under 500 leaves (see Appendix 2 for the results of our sensitivity analysis). We found out 100 leaves to be a good trade-off between accuracy and speed. For the sake of clarity of our analysis, we focus on a risk-neutral decision maker and apply a risk-neutral discount rate.

We additionally run two types of sensitivity analysis. First, we quantify the difference between the real options and the classical net present value approach. For the latter, we force the farmer to make the ultimate decision on planting, harvesting and reconversion immediately, based on the expectations of biomass output price, i.e. we switch from stochastic to deterministic model. The stochastic process for the biomass price stays the same. Second, we analyse the influence of the observed biomass price on the farmer’s decision making. In particular, we shift the constructed scenario tree up and down in parallel, keeping all the other parameters constant.

5 Empirical results

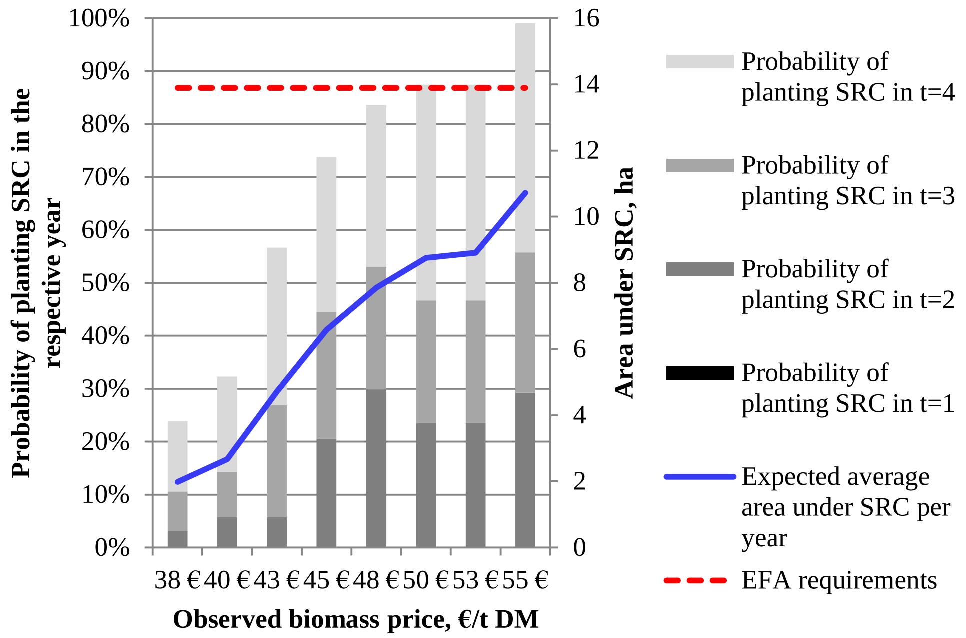
The results of our sensitivity analysis with respect to the difference between the real options and the classical net present value approach are in line with the

[7] The deterministic model is beyond the focus of the paper. Therefore we present only the major points relevant for the proposed approach, leaving out all the equations.

theory: planting trigger under the classical net present value approach is lower, than the one based on the real options. Specifically, under a now or never decision, the farmer would convert some land to SRC immediately already under a biomass price of 48 €/t DM which is 5% below our baseline scenario. In opposite to that, our real options approach finds at that price a positive option value to postpone planting which fits the observed reluctance of farmers to adopt SRC under current prices (see e.g. Bemmann and Knust 2010; Allen et al. 2014). In contrast, Musshoff (2012) reported immediate planting of SRC to be profitable in his real option application, assuming the same stochastic process for biomass price. We presume that our higher investment trigger is due to consideration of more aspects of the real world investment problems, namely full managerial flexibility in SRC cultivation along with an alternative farm activities competing for resource endowments. We next exemplify some results available from the model.

The results of the sensitivity analysis with respect to the observed biomass price (i.e. the starting value of the scenario tree) are shown in Figure 1. For instance, under the observed biomass price of 50.40 €/t DM (i.e. the baseline scenario), there is a chance of never converting any plot to SRC (the sum of probabilities is below 100%). If SRC is planted, then not immediately, specifically, SRC will be introduced in the second year with a probability of 23%, with 23% in the third year, and with 41% in the fourth year. A breakdown by the scale of investment is beyond Figure 1. If SRC is planted in the second year under the baseline scenario, in 87% of the cases a plot of 10 ha would be converted to SRC; and a plot of 20 ha in the remaining 13% of the cases. As one would intuitively assume, the (expected) area under SRC increases the biomass prices are shifted upwards (the blue curve in Figure 1). The same sensitivity analysis can be conducted for every stage of the compound option, such as harvesting and reconversion decisions, for any time points, as we account for full flexibility in planting and harvesting while considering the compound option in a farm context.

Figure 1. Sensitivity analysis with respect to the biomass output price for short-rotation coppice (SRC) for planting decision (based on the real options approach).

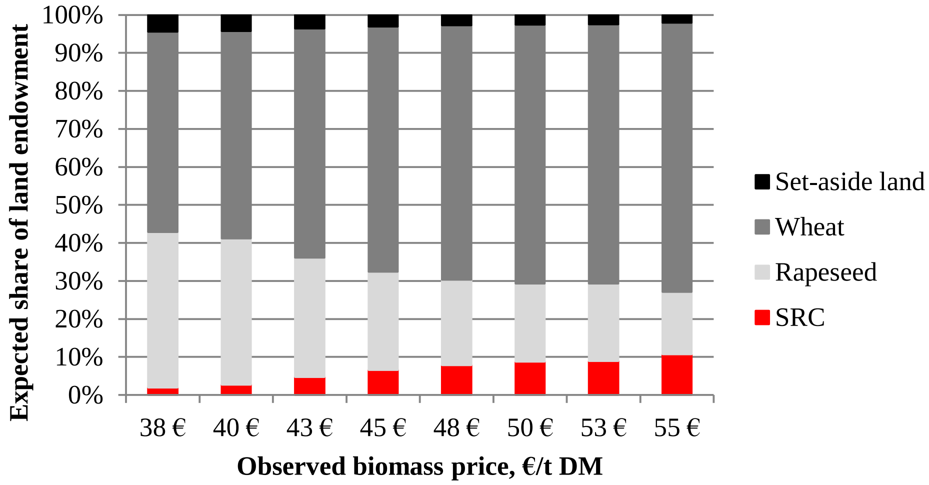


Source: own calculations and construction.

Under the presented scenarios, the EFA requirements from the Common Agricultural Policy are not fulfilled with SRC only. The red dotted line in Figure 1 indicates the acreage of SRC needed to satisfy the EFA requirements, which is always above the expected area under SRC. This means that the policy measure is not exploited fully; i.e. under the considered scenarios SRC cannot compete with alternative activities. Ignoring the policy measures and opportunity costs would have obscured this result.

The relative competiveness SRC in our analysis considers redistribution of resources between alternative activities as a consequence of investing. As mentioned above, SRC uses more land compared to set-aside as one ha of SRC only count as 0.3 ha EFA. If SRC replaces set-aside land, the labour previously used on the land that is additionally required for SRC is partly freed. Thus, adopting SRC allows increasing the share of labour intensive crops with a higher gross margin per hectare (wheat) on the remaining hectares and thus dampens the impact of competition for land (Figure 2)[8]. A similar result can be found if we assume that the freed labour is employed off-farm. Due to that effect, the investment trigger is reduced compared to a simpler model where only competition for land is reflected. Again, this result is only possible due to taking into account alternative activities, policy measures and farm constraints.

Figure 2. Expected land distribution (average per year) between alternative farm activities under different starting (observed) value of the scenario tree (based on the real options approach).



Source: own calculations and construction.

To this end, our empirical results are in line with the observed reluctance of farmers to convert to SRC under current market and policy conditions and reveal additional information on incentives to adopt SRC.

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[8] It is important to emphasize that Fig.2 illustrates the expected mean land distribution over the simulation period. Although SRC is expected to be cultivated e.g. under the baseline condition (when the observed biomass price is equal to 50 €/t DM), it is not planted immediately, but the decision is rather postponed.

6 Discussion

The proposed approach provides a detailed investment analysis, including timing and depth of exercising every stage of the compound option. Timing is represented by the optimal investment behaviour at each given node of the scenario tree, as well as at the subsequent nodes assigned with probabilities and conditional to the antecedent developments. Depth is expressed in fractional units or – if investment options of predefined sizes are considered – as the exercised subset of all the available options. At each node of the scenario tree the value to postpone can be evaluated by comparing the expected payoffs with and without temporal flexibility, i.e. the payoffs derived based on the real options and on the classical net present value approach. We also reveal additional (dis-)incentives to invest that were obscured previously due to restricted assumptions, such as interactions of alternative activities and their influence on the investment behaviour. In particular, we allow for adjustment of alternative activities or other changes in management related to exercising an option.

For the sake of clarity, we presented a simplified farm model, while it can be improved by adding more farm activities and constraints. Multiple risks, including mutual correlation, can be assumed; this would require the scenario tree to be characterized by a vector of simulated values in each node. Alternatively, several stochastic parameters can be combined in one composite risk, as done in some existing models (e.g. Flaten and Lien 2007; Bartolini and Viaggi 2012; Beraldi et al. 2013). Also, risk preferences can be considered; the easiest way would be introducing a risk utility function. Further empirical analysis can be done in different directions. First, investment triggers can be determined by conducting a sensitivity analysis with respect to any parameter of the model as a potential investment trigger. Increasing (decreasing) the respective parameter stepwise would determine an interval, within which the investment decision switches to exercising the option immediately; the true investment trigger hence belongs to this interval. The smaller the steps of the sensitivity analysis, the smaller the range containing the true investment trigger. Second, our approach allows for stepwise relaxing of the assumptions and hence quantifying their influence on the investment behaviour. Next, a comprehensive policy analysis can be done. The tested policy measures might refer not only to the investment option itself, but also to the alternative activities, as well as to the resources' endowments and other constraints. Such an analysis would reveal both direct and indirect effect of a policy measure due to redistribution of resources between alternative activities and other changes in management. Finally, if risk preferences are considered, a risk analysis can be conducted.

Our approach advances in the following. *First*, the curse of dimensionality of a binomial (trinomial) scenario tree is overcome. Our constructed asymmetric scenario tree reflects the underlying distribution, while the values are not exploding and the number of leaves is restricted. *Second*, in contrast to LSMC, our approach can be efficiently applied to problems with higher complexity. Indeed, once resources' endowments and other constraints are involved, the LSMC requires a numerical method to solve each Monte-Carlo path backwards for each stage, starting from the last one. If the size of the investment project is a decision variable as well, the LSMC additionally requires a sensitivity analysis with respect to the project size. Generating the payoffs for all potential combination of exercising time points and Monte-Carlo draws can be numerically demanding if a programming approach is needed. And not at least, that process must be programmed as well. Once it is necessary to use a programming approach to determine the NPV of a single Monte-Carlo, potentially conditional of exercising an option at a pre-determined stage, we find it more straightforward to use stochastic programming directly as proposed in this paper. Instead of approximating the payoff matrix with a regression function as in the LSMC, we approximate the Monte-Carlo fan based on tree reduction, which we judge as more transparent. *Third*, as our case study underlines, the approach is rather general. It is able to value even complex compound options such as choosing the best combination from a portfolio of different investments which interact or even problems where the number of stages is not pre-determined. There are no restrictive methodological requirements associated with our approach. Indeed, any underlying stochastic process can be assumed as long as it is possible to run Monte-Carlo simulations and to construct a reduced scenario tree. The number of stages is not limited either, unless the relations between the stages cannot be captured in equations. The time horizon is a parameter of the model and its choice is not restricted. Next, European options can be valuated using our approach in a similar way as American option. *Finally*, our approach allows conducting comprehensive sensitivity, policy and risk analyses, while representing the outcomes in a transparent and intuitive way.

There are three issues worth additional comments. First, an exploding stochastic process cannot be assumed, since a Monte-Carlo simulation might quickly lead to unrealistic values. For instance, Geometric Brownian Motion and Arithmetic Brownian Motion – common assumptions in the literature for stochastic biomass price (e.g. Kallio, Kuula, and Oinonen 2012; Di Corato, Gazheli, and Lagerkvist 2013) - exploit by simulating over several time periods. Since such simulated values are not plausible, this limitation refers to the assumption itself, rather than to the approach. Another issue that requires further research is the choice of the number of leaves. As mentioned above, there is no well-established procedure to determine the optimal number of leaves. Finally, the appropriate risk-adjusted discount rate applied to a scenario tree should differ from the risk-adjusted discount rate applied to the underlying asset, since a tree does not correctly represent the underlying volatility (e.g. Lander and Pinches 1998, p.553). In addition, as mentioned above, a tree is characterized by decreasing risk when approaching the leaves. Further research might hence focus on a method determining the appropriate risk-adjusted discount rate for a scenario tree.

7 Conclusion

The existing methods of real options valuation miss to capture the complexity of large real-world investment projects consistently. This limitation leads to reluctance of practitioners to employ the real options theory for investment analysis. In this paper we develop a numerical method for valuation of (compound

American) real options. The approach combines and benefits from both intuitive scenario tree approach and the Least Squares Monte-Carlo – the two well-known approaches for valuation of American options. Yet in contrast, our approach has no curse of dimensionality, does not require additional assumption about the functional form of Lagrangian, and ensure computational efficiency by restricting the solution domain. In addition, our approach, as well as the obtained results, is very straightforward and comprehensible.

The approach we propose can be summarized with four main steps. First, we define the decision variables of the problem. Second, we establish the relations between these decision variables, including lagged relations between time points, and combine them into a deterministic programming model. Third, we choose an appropriate distribution for the stochastic parameter(s), draw Monte-Carlo scenarios and construct from them a reduced scenario tree with probabilities, employing a scenario tree reduction technique. Finally, we employ stochastic programming for the real options valuation. The obtained results include both timing and depth of exercising options. Timing is represented by the optimal investment decision at each given node of the scenario tree and at the subsequent nodes with assigned probabilities. Depth is reflected by the optimal scale of exercising an option, taken into account opportunity costs, returns-to-scale, resources' endowments and other constraints. Our approach also allows conducting comprehensive sensitivity, policy and risk analyses, while representing the outcomes in a transparent and intuitive way.

We illustrated the approach with valuation of option to adopt, harvest, and then reconvert perennial energy crop in the farm-level context. The empirical model differs from existing investment analyses of perennial energy crops cultivation by a number of simultaneously relaxed assumptions. In particular, we allow for full flexibility in planting and harvesting, consider alternative farm activities, as well as take into account resources' endowments and other constraints. Our empirical results are in line with both the real options theory and the observed reluctance to adopt perennial energy crops. Due to relaxed assumptions, we obtain more plausible results and reveal additional incentives for perennial energy crops cultivation, in particular redistribution of resources between alternative activities. The model we presented here can be improved further, including consideration of more alternative activities and farm constraints, as well as introduction of multiple risks and risk preferences.

Our approach can be employed to various applications, being especially advantageous for real options valuation, where not only timing, but also the scale and interaction with constraints and alternative activities matter.

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Appendices

Appendix 1. Data and parameters

Parameter	Units	Assumed value
Short-Rotation Coppice		
Labour requirements	Labour units / ha	0
Planting costs	€ / ha	2875.00
Biomass growth function		
Multiplier for last year's biomass	-	1.54
Constant increase per year	t DM / ha	6.68
Harvesting costs		
Fixed costs a farm level	€	66.75
Quasi-fixed costs for each plot	€ / ha	272.13
Variable costs, depending on harvested quantity	€ / t DM / ha	10.67
MRP for logarithmic output price ($\ln P_t$)		
Starting value	-	3.92
Average value	-	3.92
Speed of reversion	-	0.22
Variance of Wiener process	-	0.22
Reconversion costs	€ / ha	1400.00
Density of trees	Number of trees / ha	9000
Alternative agriculture		
Net annual cash flow from traditional agriculture		
Winter wheat	€ / ha	537.15
Winter rapeseed	€ / ha	460.64

Set-aside land	€ / ha	-50.00
Labour requirements[9]		
Winter wheat	Labour units / ha	5.32
Winter rapeseed	Labour units / ha	4.16
Set-aside land	Labour units / ha	1
Farm characteristics		
Land endowment[10]	ha	100
Labour endowment[11]	Labour units	455
Real risk-free discount rate	%	3.87

Source: based on Musshoff (2012); Faasch and Patenaude (2012); Wolbert-Haverkamp (2012); Pecenka and Hoffmann (2012); Schweier and Becker (2012); Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V. (2016); Statistisches Amt Mecklenburg-Vorpommern (2016).

Two elements in the parameterization are worth further comments. First, we take the yield function from Ali (2009), introduce some required parameters and regress from there a linear function for biomass stock that depends on previous year's stock. Second, based on Schweier and Becker (2012) and Pecenka and Hoffmann (2012), we derive harvesting cost separated by (a) costs at farm (fixed)

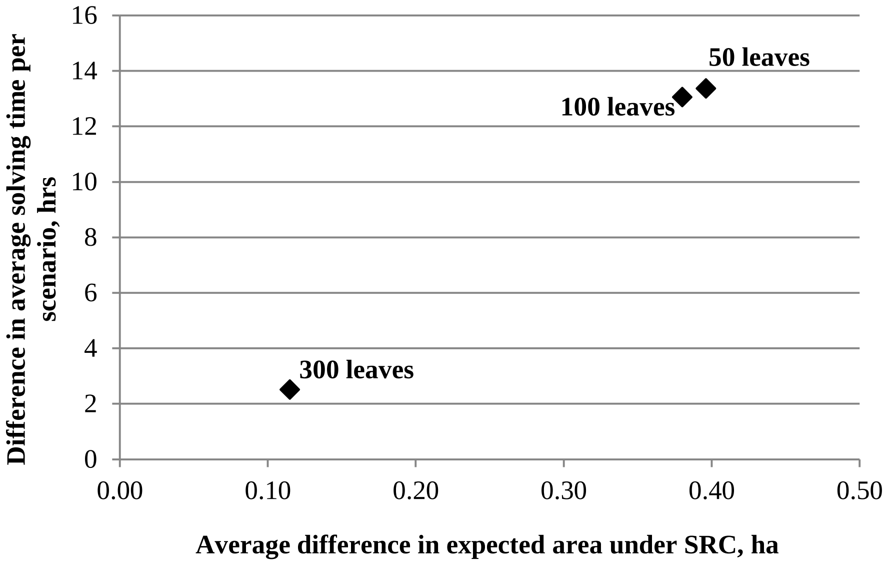
[9] Those include only field work and exclude management work, which is assumed to be limited per farm and hence have no effect on resources' distribution.

[10] The assumption is based on the statistical data, according to which 20% of agricultural farms in 2010 in Mecklenburg-Western Pomerania operated on an area of 50 to 200 Ha (Statistisches Amt Mecklenburg-Vorpommern 2016).

[11] Based on the assumption that initially 47.5% of land are devoted to winter wheat, 47.5% - to winter rapeseed, and 5% - to set-aside land. This endowment excludes management work and off-farm work; both are assumed to be limited per farm and hence have no effect on resources' distribution.

and (b) per plot (quasi-fixed) plus (c) costs per ton of harvested biomass (variable), in order to consider possible economy of scale.

Appendix 2. Comparison of solving time (for 7 price scenarios) and average expected area under SRC between the model with 500 leaves and the models with fewer leaves in scenario tree



Note that solving time for each price scenario was restricted by 20 hours. Source: own calculations and construction.