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Competitiveness of advanced and conventional biofuels: Results from least-cost modelling of biofuel competition in Germany

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ABSTRACT

Techno-economic variables for advanced biofuels produced from lignocellulosic biomass have been scrutinized and combined with a newly developed transparent model for simulating the competitiveness between conventional and advanced biofuels for road transport in the medium to long term in Germany. The influence of learning effects and feedstock cost developments has been highlighted, including also gaseous fuels. Thorough sensitivity analyses were undertaken. Previously reported cost assumptions for advanced biofuels were found to have been too optimistic. The most cost-competitive biofuels for most of the time period remained conventional biodiesel and bioethanol, but the costs of these options and biomethane and Synthetic Natural Gas (bio-SNG) converged in the medium term and thus other factors will play a decisive role for market developments of biofuels. Feedstock cost uncertainties for the future remain a challenge for long-term planning, and low-cost short-rotation coppice may change the picture more than any other parameter. Of the advanced biofuels, bio-SNG was found significantly more cost-competitive and resource efficient than Fischer-Tropsch-diesel and lignocellulose-based ethanol, but still requiring a dedicated long-term policy. The results and the large sensitivities of biofuel competitiveness stress the need for more data transparency and for thorough sensitivity analyses of the results in similar system studies.

1. Introduction

Global concern for climate change calls for alternatives in the transport sector, which accounts for 14% of global anthropogenic (IPCC, 2014) and 20% of German GHG-emissions (BMWi, 2013). Germany aims to reduce transport emissions by 6% until 2020 (BImSchG, 2014), with subsequent further emission reductions required in order to meet overall climate targets (UNFCCC, 2015). Aside from demand reduction and modal shift, biofuels and a switch to electric mobility are the main renewable solutions for road transport, with biofuels fitting comparably well into the current vehicle fleet.

The presently dominant biofuels in the German road transport sector are biodiesel from oil bearing crops and bioethanol from sugar beet or grains. These conventional biofuels compete with food production (see e.g. Foley et al., 2011) and have a limited GHG-abatement even when excluding indirect land use effects (Cherubini et al., 2009). Advanced biofuels derived from biomass with a high share of cellulose, hemicellulose and/or lignocellulose potentially avoid these problems and are thus often proposed as a solution, with promising future cost estimates reported (Chum et al., 2011, p.282; Eisentraut et al., 2011, p.32; IEA, 2008, p.335). However, to date advanced biofuels have not yet become commercially available, and large-scale attempts have failed (Hogan, 2011).

The capital investment and production costs of advanced biofuels have been subject to a large range of estimates (Haarlemmer et al., 2012). The future cost development is subject to the development of feedstock costs and to learning effects, both being uncertain. At any point in time, the biofuel options are also subject to competition between each other to fulfill biofuel mandates. Yet - to our knowledge - the effect of these uncertainties on cost developments and competitiveness of biofuels have not been thoroughly assessed before.

There is a large number of future modelling studies including biofuels, with a wide array of different scopes and results (Börjesson et al., 2013). The models are often large and the focus often on whether to use biomass in the power or transport sector (as Martinsen et al. (2010) did for Germany) and thus the techno-economic details of the different biofuels have not been central (Börjesson et al., 2013). Wit et al. (2010) performed a modelling study including learning and competition between biofuels for transport in Europe. However, the model did not build the yearly development on prevalent capacities,

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thus missing out on path-dependencies, gaseous biofuels were excluded and advanced liquid fuels were seemingly assumed to be lower cost than conventional biofuels already from the beginning of the time-period, indicating a need for further scrutiny of the data basis. Most other models are optimisation models with perfect foresight, thus losing information regarding learning effects and path dependencies, which are of value to policy makers. Also, there is a lack of thorough sensitivity assessments to results in energy systems modelling (Hedenus et al., 2012). This is perhaps of particular importance in the bioenergy sector, which is subject to influence from numerous parameters.

To address the open points mentioned above, a sound data set has been developed and used as a basis for a newly developed least-cost myopic simulation model in order to answer the research question: Which liquid or gaseous biofuel options from domestic biomass are potentially most cost-competitive in Germany in the medium to long term?

2. Methodology, scenarios and data

Three pathways of conventional biofuels (biomethane produced from maize, bioethanol from sugar beet and biodiesel from rape seed) and three pathways as advanced biofuel counterparts (Synthetic Natural Gas (bio-SNG), bioethanol from lignocellulosic biomass (Ligno-EtOH) and Biomass-to-Liquid (BtL)/Fischer-Tropsch (FT)-diesel, all produced from biomass with high lignocellulosic content) were included in the simulation. All biofuels were assumed to be equivalent at the end user stage (with some differences regarding transport and storage costs).

Vehicle costs are neglected in this paper, as various and possibly fuel type specific strategies for implementing biofuels can be foreseen in a likely rapidly changing market (see e.g. Economist (2016)), which highly affect vehicle usage rates and efficiencies and have large consequences for the vehicle cost added to the fuel cost.

Germany has relatively much experience with the conventional biofuel options biomethane, bioethanol and biodiesel, the data for which are elaborated in Thrän et al. (2015). For advanced biofuel options there is less experience, why a literature review was additionally performed in order to come up with estimates for techno-economic parameters. All costs used in the modelling were converted to €$_{2010}$.

2.1. Model description

In order to model the competition between different technology options, a simulation model has been developed. BENSIM (BioENergy SImulation Model) is a myopic recursive dynamic bottom-up least-cost simulation model with endogenous technological learning, seeking the least-cost mix of biofuel production options on a yearly basis for fulfilling a set demand. Through the recursive elements of learning effects and previously built capacities, path dependencies can be captured by the model.

The existing biofuel plant infrastructure in the region in focus (here Germany) is the basis at the starting point of the modelling. For each year of the simulation, BENSIM starts by removing the plants that have reached the end of their life-time (capacities present at the beginning are assumed to be decommissioned linearly over the life-time of the plants). In the next step, the technology options are sorted in the orders of total costs (TC; Eq. (1)) and in merit order after marginal costs (MC; Eq. (2)). A given biofuel demand sets the limit for the production and is also the basis for calculating a minimum market price (p_{sys}), defined by the MC of the most expensive option in the merit order which is put into production. If there are options which have TC lower than the p_{sys}, capacity investments[1] take place, beginning with the option with the lowest TC.

This continues until the market price adjusts on a level below the TC of still available options and the system reaches a (partial) equilibrium. In order to account for e.g. regional differences, investment risk behaviour and market imperfections, options with TC within 10% of the least-cost alternative are treated equally with the least-cost option, i.e. they are also invested in during the same round. There are no capacity expansion constraints in relation to previously built capacities.

After the investment phase, biofuel production takes place following the merit order based on marginal costs of production, until the hypothetical biofuel target is fulfilled (and/or until a given biomass potential is exhausted). In the following year, the technology options that experienced an expansion are subject to learning effects, reducing the investment costs by the learning rate for each doubling of capacity. The options which were not expanded experience "exogenous" learning through a research and development mechanism, defined as one learning rate unit in a specified number of years.

Eq. (1) shows the investment cost $I_j^{(t)}$ [€ GJ$^{-1}_{fuel}$] for technology *j* at timepoint *t* as a relationship of the initial investment cost $I_j^{(0)}$ [€ GJ$^{-1}_{cap,fuel}$ converted from € MW$^{-1}_{cap,fuel}$] with an assumed capacity factor $C_{f,j}$ and an annuity factor with an assumed discount rate *i* over a set time-span T, including a learning effect by a learning rate LR_j with increasing cumulative production capacity $k_j^{(t)}$ divided by the initial capacity $k_j^{(0)}$ (see Grubler (1998, p81ff) and IEA (2000)). This relationship holds with the assumption that relative expansion in the region in focus (Germany) is equal to the relative expansion globally. In order to have a nonzero denominator, a virtual initial capacity $k_j^{(0)}$ for options not presently at the market is set at 2 PJ in this paper, whereas actual initial capacities are set to zero. As the starting capacity for these options is relatively small, the capacities multiply relatively quickly in case of investments and thus can experience substantial learning.[2]

$$I_j^{(t)} = \frac{I_j^{(0)}}{C_{f,j}}\frac{i\,(1+i)^T}{(1+i)^T-1}\left(\frac{k_j^{(t)}}{k_j^{(0)}}\right)^{-\log_2(1-LR_j)} \tag{1}$$

$$MC_j^{(t)} = c_{om,j}^{(t)} + \frac{p_f^{(t)}}{e_f\,\eta_j^{(t)}} + p_{f2}^{(t)}\dot{m}_{f2,j} + p_{el}^{(t)}\dot{m}_{el,j} + p_{th}^{(t)}\dot{m}_{th,j} + c_{log,j}^{(t)} - p_{bp,j}^{(t)}\dot{m}_{bp,j} + p_{CO_2}^{(t)}\dot{m}_{CO_2,j} \tag{2}$$

Eq. (2) shows the marginal cost $MC_j^{(t)}$ [€ GJ$^{-1}_{fuel}$] for technology *j* at timepoint *t* as a sum of operation and maintenance costs and personnel costs $c_{om,j}^{(t)}$, costs for main feedstock ($p_f^{(t)}$ [€ t$^{-1}_{DM}$] divided by feedstock specific energy content e_f [GJ t$^{-1}_{DM}$] and conversion efficiency $\eta_j^{(t)}$), secondary inputs $p_{f2}^{(t)}$ [€ t^{-1}], electricity ($p_{el}^{(t)}$ [€ kWh^{-1}] multiplied by amount required, $\dot{m}_{el,j}$ [kWh GJ^{-1}]), process heat ($p_{th}^{(t)}$ [€ kWh^{-1}] multiplied by amount required, $\dot{m}_{th,j}$), logistic cost $c_{log,j}^{(t)}$, a credit for by-products $p_{bp,j}^{(t)}$ and a cost of GHG-emissions (the price of emissions $p_{CO_2}^{(t)}$ multiplied by amount emitted $\dot{m}_{CO_2,j}$).

Eq. (3) shows the constitution of total costs as a sum of investment and marginal costs.

[1] Investments take place in units of 1 PJ$_{cap}$ a^{-1} (ca 35MW$_{cap}$ at 8000 full-load hours), an assumption which enables a competition on equal terms. Typical plant sizes for the included options range between 7-250 MW (Ponitka et al., 2016) and thus the model units do not correspond to whole plants, but in some cases more and in some less. However, as the additional demand to be fulfilled surpasses at least 8 PJ a^{-1}, options with typically large plants may reach realistic capacity increments, especially when taking the development over time into account. Similarly, for options with typically small plant sizes the model unit corresponds to several plants.

[2] The set biofuel target influences the amount of expansion possible, thus limiting the possible cost reductions through technological learning. If the final biofuel target of 400 PJ is met by one of these technologies, about 9 virtual capacity doublings are possible, translating into a ca. 60% investment cost reduction with a 10% learning rate, which may be seen as a rather high reduction but in line with some estimates for future costs (see e.g. Haarlemmer et al. (2012) and Hamelinck et al. (2005)).