# Progress

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## Deliverable

**D 3.2 -** Model – reference simulations and sensitivity analysis results

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**About PROGRESS**

PROGRESS is a coordination and support action for the European Commission and aims to support and accelerate the deployment of Industrial Biotechnology (IB) in the EU industry by identifying high-value opportunities for IB and proposing actions to address them successfully. For that purpose, we will first provide a comprehensive and dependable information base (including modelling and simulation approaches) which allows for plausible estimations on the future of IB in the EU in the short and medium-term. Second, in collaboration with stakeholders we will elaborate a future scenario and a common vision for IB in Europe containing the most promising value chains, related R&D&I needs and necessitated policies for IB in Europe. Based on these steps, we will provide strategic advice for research, industry and policy making regarding potential issues and topics for collaboration, future policy programmes, the required technological infrastructure, capabilities, and economic structures. A main focus will be to identify opportunities for collaboration between EU member states and proposed actions to increase awareness and incentives for those collaborations. For more information see www.progress-bio.eu

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# Content

# 1 Objectives and methodology

## 1.1 Objectives

The current Deliverable contains the results of System Dynamic modelling for selected value chains in Industrial Biotechnology (IB). The related tasks have been embedded in the project PROGRESS as follows.

The objective of the former WP2 was to elaborate and assess selected value chains for industrial biotechnologies - in promising industrial biotechnologies segments - providing thereby a detailed overview of the European capacities, R&D&I opportunities, technological and non-technological (e.g. economic, demand, political, social) bottlenecks. Based on results, two most promising bio technologies were selected for further detailed analysis:

- **Lignocellulosic ethanol**
- **Bio-based plastics**

In order to explore the relationships and dynamics between key factors for the future developments of selected IB, as well as to explore future paths and the impacts of changing policies and framework conditions, a System Dynamics modelling and simulation approach was conducted. The research process was organised as follows.

In **WP3 of the PROGRESS CSA** a system dynamics model was elaborated, validated and calibrated. The aim was, on the one hand, to provide an objective assessment of the relevance of different factors for the deployment of both selected IB for extensive market opportunities. On the other hand, the dynamics and inter-linkages between defined factors were assessed. Data generated in earlier work packages represented thereby the main input for modelling. Following, the models for both value chains were calibrated, their developments in the past decade reproduced, and potential reference developments for the short/middle term analysed. This approach yield information on the impact of different factors on development of the value chain and the demand for both selected IB value chains.

Afterwards, in **WP4**, future paths of realistically achievable developments were analysed and scenarios elaborated for value chains of both selected IB. The impact on markets of these future paths were then simulated in a refined version of the System Dynamics model. Moreover, sensitive analyses were conducted to show which consequences could be expected from potential changes of different factors (e.g. the impact of certain policies, changes in demand or capacities, different customer awareness). Hence, the aim was to model the impact of consistent future scenarios for the value chains of both IB to draft implications for recommendations in later stages of the PROGRESS project WP 5.

## 1.2 Methodology

System Dynamics (SD) was developed in the late 1950s by Jay W. Forrester at the Massachusetts Institute of Technology (MIT). It represents a modelling methodology that allows analysing dynamics of socio-economic systems and simulating their long-term trends. At the core of this methodology is the Control and Information Theory, while the Descriptive Decision Theory and the computer-aided simulation provide its technical basis (Forrester 1968; Forrester 1971; Milling 1984). Due to its configuration, SD enables to represent a holistic picture of system processes in one model by using differential equations, describing thereby all relevant material, financial, and information flows (Forrester 1971). Hence, SD approach is suitable for researching dynamic problems from a great range of fields, e.g. business, social, economic, biological and ecological (Sandrock 2007).

Alike to the paradigm of Control Engineering, SD also ensures that each information-based decision calls for a feedback within the system, whereby the current system state is changed. Common approaches of decision theory assume that the decision maker always decides rationally. Such an assumption, however, by no means corresponds to reality and may distort the result. Dealing with this issue, SD models are based on Descriptive Decision Theory and postulate that the human being as the decision maker will not inevitably make rational decisions. With other words, SD models are able to account for irrational decision systems (Schröter 2006) which especially refers to uncertainty and incomplete information in social innovation processes. The method also enables reliable assessments despite complex effects from feedback coupling structures, time delays, and aggregations as well as general cases of non-linearity. Thus, it overcomes the natural tendency of man towards linear thinking (Dörner 1989; Sterman 1989; Paich 1993; Sterman 2001). By means of continuous computer-based simulation however, the dynamic behaviour of a system and the individual parameters can be analysed. The system‘s understanding of the effects of past decisions is thereby deepened and the interaction of the individual variables becomes more transparent (Forrester 1968; Stumpfe 2002; Milling 2002).

SD is thus a scientific method that enables an ex-ante examination and evaluation of long-term impacts of decisions on a system as well as the existing interactions within the system under different environmental dynamics (Larsen & Bunn 1999). The possibility to evaluate decisions based on if-then analyses constitutes an additional benefit. SD furthermore offers the advantage of considering variables that are difficult to quantify but relevant for the system. In order to quantify such variables, expert assessments could be employed and the results integrated in modelling process (Ford & Sterman 1998).

SD approach and simulation modelling were chosen as appropriate research method in the project because of the following features:

- for delivering valid findings for the overall CSA, the simulation model allows **formalization of relationships** between key factors by mathematical equations,
- it facilitates opening up the black box of the industrial biotechnological system for giving a deeper understanding,
- it enables **visualization and quantification of future paths** for complementing the qualitative future design of the value chain scenarios in the PROGRESS CSA,
- it allows various **explorative simulations under different frame conditions** for illustrating a holistic solution space and
- it facilitates **decision making** for policies on quantified, mathematical based forecasts for the recommendations.

Due to these features SD modelling and simulation is a powerful tool in order to support policy design and to give recommendations for action for supporting the desired technological and economical effects.

In order to represent the models and the results of simulation and sensitivity analysis as detailed as possible, in the following the value chain models for selected IB are presented one after another in two chapters. Both chapters are thereby organised as follows.

First, based on desk-top research as well as on results of the scenario workshop the main interactions of variables are presented and objectives defined in terms of the related issues. These interactions are used further to construct a causal loop diagram which forms the basis for the stock and flow mathematical modelling. Following that, simulation runs and sensitivity tests are conducted to analyse the impacts of individual factors and to obtain first insights into the system's behaviour. The last section looks at conclusions, which can be drawn from these findings.

# 2 System Dynamics modelling of the European demand for lignocellulosic ethanol

## 2.1 Introduction

Currently biofuels contributed significantly to goals for renewable energy and ambitious greenhouse gas emission reduction targets in Europe. Nevertheless, first generation biofuels have also been highly criticized due to food vs. fuel debates – direct and indirect change in land use (LUC and ILUC). Moreover, biofuel's sustainability qualities have been disputed (Timilsina & Shrestha 2010). A key approach to the path to more sustainable development is the continuous switch to second generation biofuels which are derived from non-food resources. One of the most promising biofuels is lignocellulosic ethanol that may be produced from agricultural residues (e.g. straw and corn stover), other lignocellulosic raw materials (e.g. wood chips) or energy crops (miscanthus, switchgrass, etc.) (ePURE 2016).

Today, the global production of second generation (2G) ethanol[1] is still very low, but increasing, as several new 2G facilities have become operational in the last 3 years (Bio-Tic 2015; UNCTAD 2015).[2] One full commercial plant is operative in the EU (Beta Renewables in Italy), which accounts for somewhat less than 1% of the overall ethanol production capacity in Europe (Philips et al. 2016). Still, significant technological challenges in the build up of commercial plants occur. In particular, cost competitiveness compared to 1G generation biofuels and fossil fuels has not been achieved yet, as some production steps (e.g. pre-treatment of cellulosic), are still not optimized.

Because of absence of cost competiveness, the lignocellulosic bioethanol market is strongly dependent on policy support, mainly on quota obligations for biofuels (Bio-Tic 2015). In 2015, the European Commission (EC) amended the Renewable Energy Directive and officially introduced a seven percent cap (=share of biofuels in total fuels) on food based biofuels thus limiting future production of these first generation biofuels, and introduced an indicative, non-binding 0.5% sub-target for second-generation of biofuels (double counted towards the 10% renewable target in transport). However, these indicative targets have not led to a strong market pull yet. At the end of 2016, the European Commission published a proposal for a new Renewable Energy Directive (RED II), where an obligation of 3.6 % for 2G generation biofuels is envisaged. Currently, uncer-

[1] We are using second generation (2G) ethanol as synonym for lignocellulosic ethanol

[2] For more information on the value chain, see Deliverable 2.2 and 4.1 on pwww.progress-bio.eu

tainties regarding future regulations still exist and so does the outlook for second generation lignocellulosic ethanol in Europe (see e.g. OECD & FAO 2016; Bio-Tic 2015; Hirschnitz-Garbers & Gosens 2015).

Even without reaching full cost competitiveness, the production cost for lignocellulosic ethanol will have an important role for market development, as it is more likely that envisaged quotas will be actually transferred into national regulation and fulfilled or slightly overachieved in reality. Once again, production costs are highly dependent on the potential (policy-induced) market size. A significant amount of literature has studied potential costs reduction from scale and learning effects and assumes significant reductions. This in turn may lead to convergence compared to 1G biofuels and fossil fuels in around roughly 15-20 years (e.g. IEA-ESTAP & IRENA 2013; Daugaard et al. 2015; Festel et al. 2014; Jonker et al. 2015).

For an analysis of that convergence, a System Dynamics approach is well suited (Vimmerstedt et al. 2012; Barisa et al. 2015). Therefore, a System Dynamics model was developed which aims to analyse the following research question:

- *How does the linkage between the policy-induced market growth and the reduction in production costs resulting from learning effects influence the dynamics of demand for lignocellulosic ethanol in Europe?*
- *What are the effects of the scenarios elaborated in the PROGRESS CSA on lignocellulosic ethanol?*

## 2.2 Model conceptualisation

To develop a system structure that links policy-incentives and learning effects on 2G ethanol demand, we built a causal loop diagram with three subsystems:

1. Effects of policy driven demand on overall 2G ethanol demand
2. Learning and scaling effects on production costs
3. Effects of feedstock costs on production costs

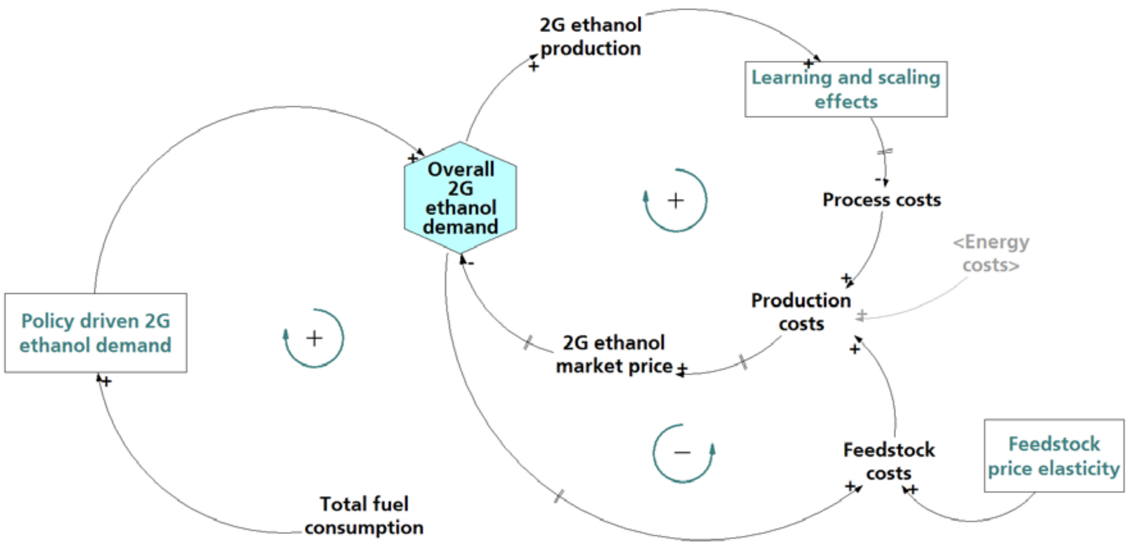
### 2.2.1 Causal loop diagram of demand for 2G ethanol

As starting point for modelling the demand for 2G ethanol (see figure 1) we used policy driven demand for 2G ethanol which is derived from the initial total fuel consumption based on the indicative targets (EC 2016).

As the production costs, and thereby the price for 2G generation ethanol, depend on the potential (policy-induced) market size, we use the initial demand for 2G ethanol as a starting point for the second subsystem, reflecting the demand on production capacities (see figure 1). Furthermore, with increased production capacities, the process costs of the ethanol production decrease.

The reason for this cost reduction is dynamic scaling and learning effects resulting from production scale size and technological process improvements. These effects have been discussed intensively for biomass-based innovations such as lignocellulosic ethanol because of their rather low technological maturity compared to established oil-based products (Ye et al. 2014; Festel et al. 2014). Potential aspects for improvement regarding the production of lignocellulosic ethanol relate to a more efficient organization of production and transportation processes, the use of advanced materials, lower costs of the enzymes for pre-treatment processes and lifetime prolongation of catalysts (De Wit et al. 2010). Techno-economic literature for biomass technologies has commonly accepted the experience curve approach to estimate the aggregated effect of technological learning over future time periods. According to this concept, costs decline by a fixed percentage amount with each doubling in cumulative production (De Wit et al. 2010; Festel et al. 2014).

**Figure 1:** Causal loop diagram for 2G ethanol demand

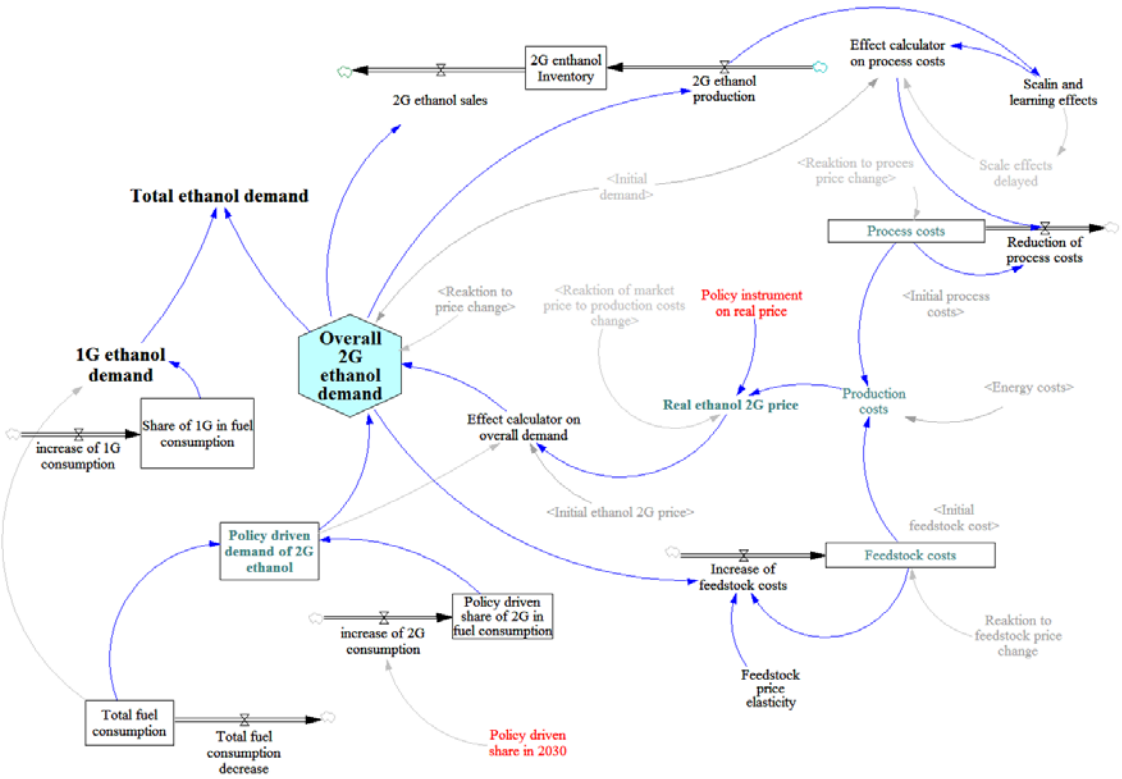



The third sub-system represents the effects of feedstock costs on production costs (see figure 1). The feedstock costs depend, on the one hand, on the overall demand for 2G ethanol and, on the other hand, on the price elasticity.

### 2.2.2 Stock and flow diagram for 2G ethanol demand

Based on the conceptual models of two above presented subsystems (se figure 1) we build a simulation model on the VENSIM software platform.

**Figure 2:** Stock and flow diagram of the demand for 2G ethanol




As starting point for modelling we defined demand for 1G and 2G ethanol based on policy-driven shares in total fuel consumption (EC 2016).

$$Q^{1G}(t) = TFC(t) * S^{1G}(t) \tag{1.1}$$

where:

| | | |
|---|---|---|
| $Q^{1G}(t)$ | Demand for 1G ethanol | *[Million litres / Month]* |
| $S^{1G}(t)$ | Share of 1G ethanol in total fuel consumption | *[Dmnl]* |

For modelling the policy-driven demand for 2G ethanol we used following indicative targets (EC 2016):

**Table 1:** Indicative targets for 2G generation ethanol in Europe

| Year | 2010 | 2015 | 2020 | 2025 | 2030 |
|---|---|---|---|---|---|
| % of the total fuel con-sumption | 0.01 | 0.11 | 0.25 | 0.45 | 0.5 |

For calculating the yearly demand for 2G ethanol we used the model:

$$Q^{2G}_{overall}(t) = Q^{2G}_{overall}(t_0) + \int_{t_0}^{t_{240}} \left( Q_{policy}(t) * \left( 1 - \frac{P^{2G}_{real}}{P^{2G}\ (t_0)} \right) \right) dt \qquad (1.2)$$

$$Q^{2G}_{\mathrm{policy}}(t) = \mathrm{TFC}\ (t) * S^{2G}(t) \qquad (1.3)$$

where:

| | | |
|---|---|---|
| $Q^{2G}_{overall}(t)$ | Overall demand for 2G ethanol | *[Million litres / Month]* |
| $Q^{2G}_{policy}(t)$ | Policy driven demand for 2G ethanol | *[Million litres / Month]* |
| $P^{2G}\ (t_0)$ | Initial price for 2G ethanol | *[EUR/litres]* |
| $P^{2G}_{real}\ (t)$ | Real price for 2G ethanol on market | *[EUR/litres]* |
| TFC (t) | Total fuel consumption | *[Million litres / Month]* |
| $S^{2G}(t)$ | Share of 2G ethanol in total fuel consumption | *[Dmnl]* |

For modelling process costs we use scaling and learning effects whose level is based on the monthly production capacities, as explained in the first conceptual model. A noteworthy amount of literature has studied potential costs reduction from scale and learning effects and assumes significant reductions, which may lead to convergence compared to 1G biofuels and fossil fuels in around roughly 15-20 years (e.g. IEA-ESTAP & IRENA 2013; Daugaard et al. 2015; Festel et al. 2014; Jonker et al. 2015). For modelling the learning and scaling effects, we calculated from 1% to 10% in accordance with the multiplication of the production capacities compared to the start demand - from 1 time to 100 times. Because we started with a very low level of demand at the initial time (2010), and this amount increases rapidly (e.g. IEA-ESTAP & IRENA 2013; Daugaard et al. 2015; Festel et al. 2014; Jonker et al. 2015), we use low scale effects (1%) for multiplications of up to 7 times. A delay of 6 months is also integrated into the model, which indicates the time for real reduction of prices after a scale effect occurs.

$$\mathrm{C}^{2G}_{process}(\mathrm{t}) = \mathrm{C}^{2G}_{process}(\mathrm{t}_0) + \int_{\mathrm{t}_0}^{\mathrm{t}_{240}} \left(\mathrm{C}^{2G}_{process}(\mathrm{t}) * LS(t)\right) \mathrm{dt} \tag{1.4}$$

where:

| | | |
|---|---|---|
| $\mathrm{C}^{2G}_{process}(\mathrm{t})$ | Process costs | *[EUR/litres]* |
| $LS(\mathrm{t})$ | Learning and scaling effects on process costs | *[Dmnl]* |

In the third subsystem, we modelled the effect of changed production costs on 2G ethanol demand. Following the study of IEA-ESTAP and IRENA (2013) we calculated production costs as a sum of process costs (42%), energy costs (16%) and feedstock costs (42%). To simplify the model considering only the effects of process costs and feedstock costs on real price and demand, we calculate production costs as variable of the real 2G ethanol price.

$$\begin{aligned} \mathrm{C}^{2G}_{production}(\mathrm{t}) = & \left(0{,}42 * \mathrm{C}^{2\mathrm{G}}_{feedstock}(\mathrm{t})\right) + \left(0{,}16 * \mathrm{C}^{2\mathrm{G}}_{energy}(\mathrm{t})\right) \\ & + \left(0{,}42 * \mathrm{C}^{2\mathrm{G}}_{process}(\mathrm{t})\right) \end{aligned} \tag{1.5}$$

where:

| | | |
|---|---|---|
| $C^{2G}_{production}(t)$ | Production costs | *[EUR/litres]* |
| $C^{2G}_{energy}(t)$ | Energy costs | *[EUR/litres]* |
| $C^{2G}_{feedstock}(t)$ | Feedstock costs | *[EUR/litres]* |

Assuming price elasticity = 1, the model calculates the change of the 2G demand based on the difference between the initial and the calculated real price as result of the decreased process costs. As the customers do not simultaneously react to price changes, a delay of two months is integrated in the model to capture this effect.

For calculating the real price, we used the model:

$$P^{2G}_{real} = C^{2G}_{production}(t) - I^{2G}_{policy} \tag{1.6}$$

where:

| | | |
|---|---|---|
| $I^{2G}_{policy}$ | Policy instrument on real price | *[EUR/litres] based on % of real price* |

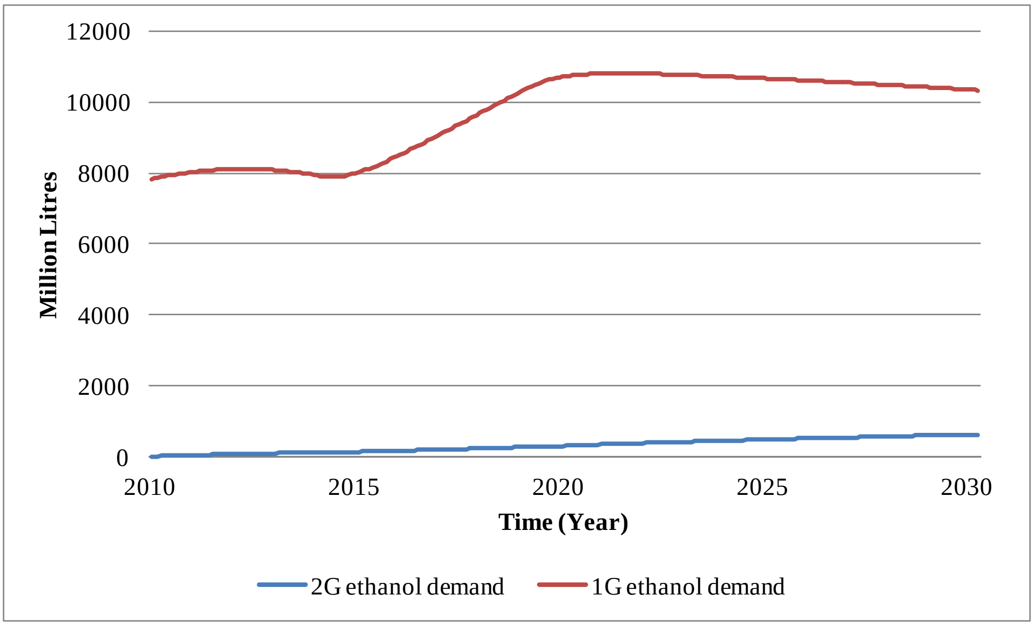
After validation tests of our System Dynamics model, in which we verified the structure of the model and validate it through extreme conditions experiments and sensitivity tests, the model is ready for first system behaviour analysis for policymaking. For a dynamic analysis and a deeper understanding of the system's behaviour, various simulation runs and tests were conducted.

## 2.3 Results of simulations

The results of the simulation runs are shown in the following and interpreted to generate the first dynamic hypotheses.

Figure 3 shows the dynamics of the 1G (red line) and 2G (blue line) ethanol demand in the time period of 240 Months starting from January 2010. For the 2G ethanol we simulate under the assumption of an indicative target – following the Renewable Energy Directive (RED II) - that the share of 2G in total fuel consumption in 2030 will be 0.5%.

**Figure 3:** Dynamics of demand for 1G and 2G ethanol between 2010 and 2030[3]




The runs in figure 3 show that 1G ethanol demand increases between 2015 and 2020, up to a level of approximately 10.500 million litres. This boost results from a higher share of 1G ethanol of the total fuel consumption in 2015, switching from 4% to 6%. After reaching its peak in the year of 2020, the 1G demand slowly decreases again, because the share remains the same, but the total fuel demand decreases from 2020 until 2030. Moreover, at around 2025 the 2G demand starts to increase slowly, reaching a level of 600 million litres in 2030. This derives from boosting the share of 2G ethanol from 0.25% in 2020 to 0.45% in 2025 and hence, it is almost doubled. However, due to this very slow increase it seems necessary to generate further simulation runs, showing the potential effects resulting from an additional initial share.

3 By policy-driven share of the 2G ethanol demand 0.5 % of the total fuel consumption (Base simulation run)

In order to gain a deeper insight into the dynamic behaviour of the 2G ethanol market and its interactive links to learning effects and policy incentives, we analysed various demand scenarios for Europe, based on the qualitative scenarios elaborated in the PROGRESS project:[4]

**Stagnant development scenario:**

The current indicative quote of 0.5% for lignocellulosic ethanol is achieved in 2030, no further political measures from the supply or demand side to foster commercial activities.

**Partial established production scenario:**

An obligatory mandate of 1.8% was assumed.

**Policy-driven expansion scenario:**

Strongly supportive policy mix with an obligatory mandate of 3.6%, financial support to build up new commercial production facilities.

Therefore, we modified the share of 2G ethanol in 2030 from 0.5% to 3.6% and compared the policy-driven demand and the overall demand of 2G ethanol (see assumptions in table 2). The policy-driven demand describes the amount of litres generated by the legal share of 2G ethanol of the total fuel demand. In contrast, the overall demand includes the legal share plus additional consumption patterns based on the market price. Consequently, the higher the learning rate, the lower the market price and hence, the higher the overall demand. This demonstrates how the legal share affects an impact on the overall demand, too.

**Table 2:** Assumptions for scenarios

| Scenarios | Policy driven share of 2G in TFD | Policy instrument - financial support |
|---|---|---|
| **Stagnant development scenario** | 0.5% | no |
| **Partial established production scenario** | 1.5% | no |
| **Policy-driven expansion scenario** | 3.6% | yes |

The following figures show the dynamics of the 2G ethanol demand, as the result of policy incentives, and the overall 2G ethanol demand, as the result of learning effects resulting in an additional 2G ethanol demand.

[4] See Deliverable 4.1 on www.progress-bio.eu

**Figure 4:** Stagnant development scenario for 2G ethanol demand (Base simulation run)

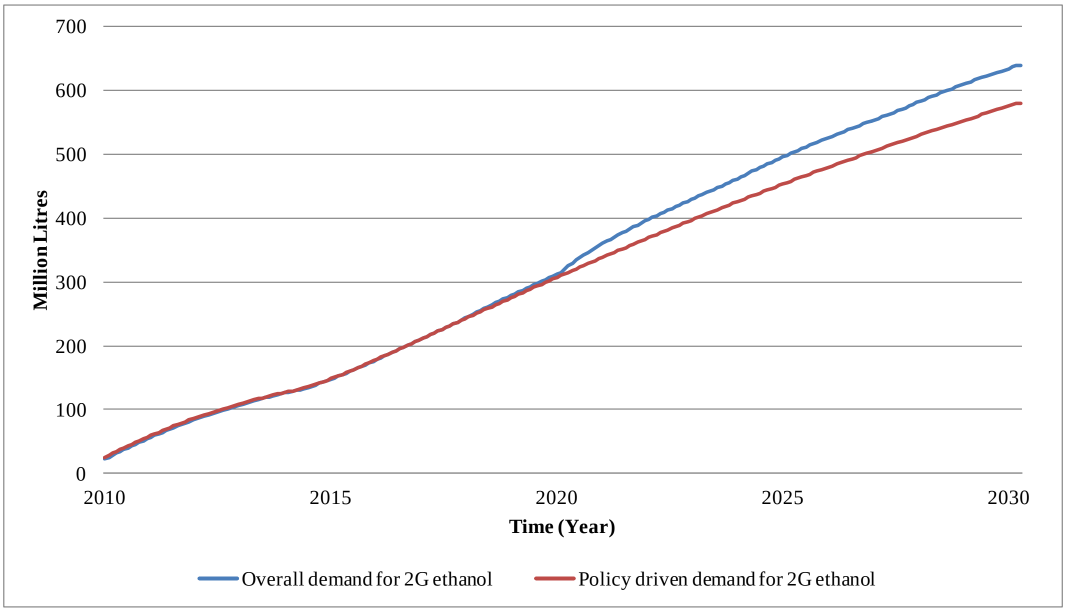
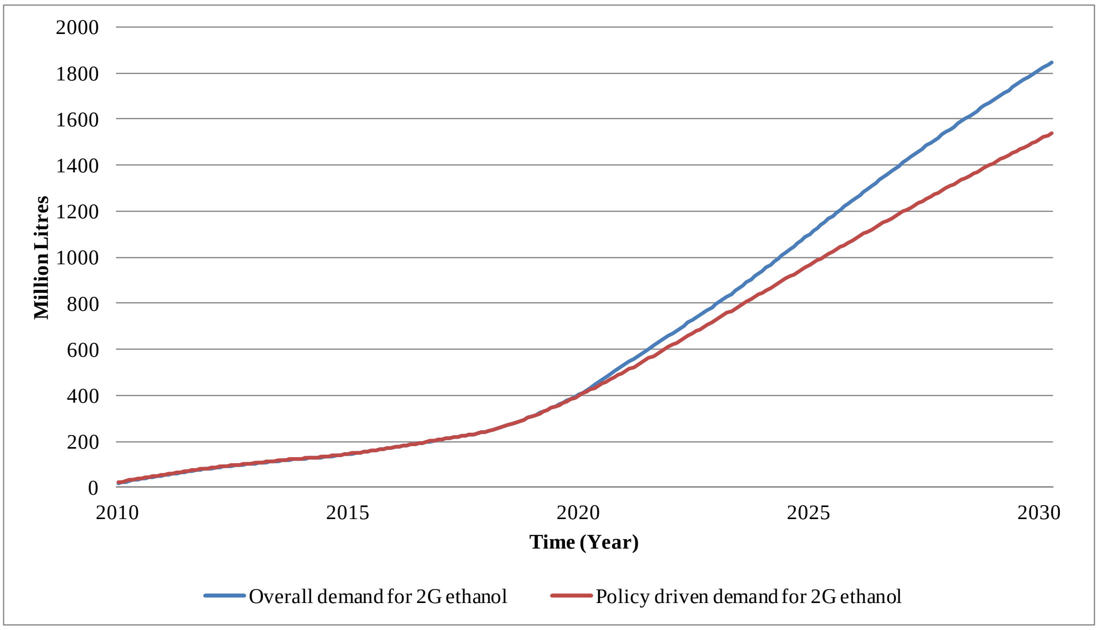


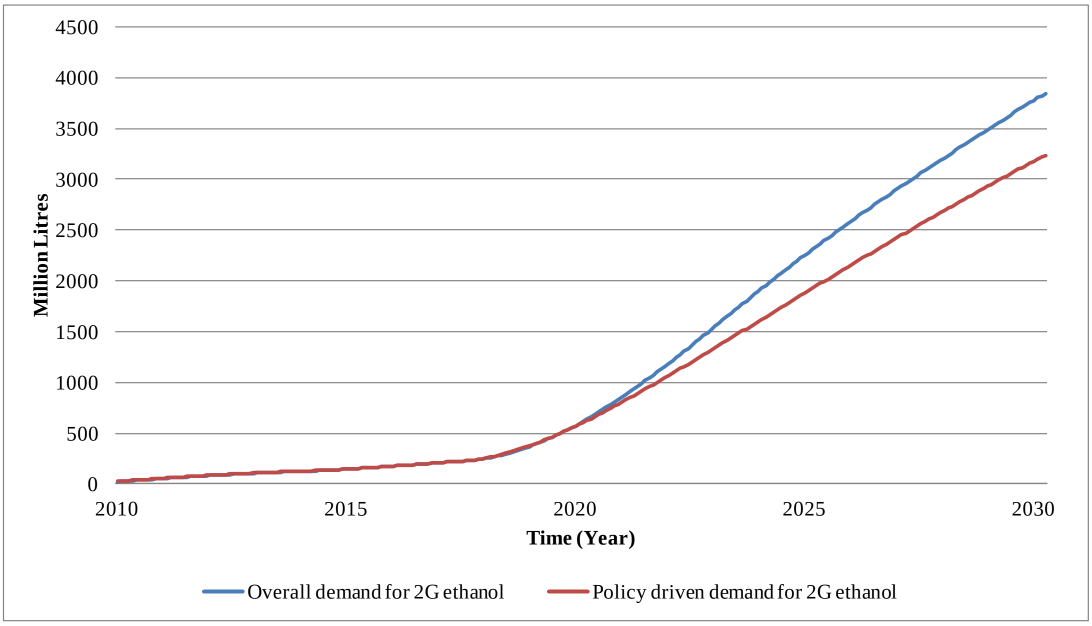

Figure 4 represents the base simulation run in which an initial share of 2G ethanol in total fuel consumption of 0.5 % was used. In 2030, it reaches a demand capacity of approximately 600 million litres and hence, almost 100 million litres more than the initial demand. Moreover, we observe the "gap" between real demand and initial demand is opening over time. These effects result from an accelerated price decrease, leading to a faster reduction of production costs and thus, a higher demand over the years. This loop is accelerating over time, which results in the demand gap further increasing over time. This loop and hence this gap, is influenced by the share of 2G ethanol reached in 2030. Consequently, the question arises, how does a higher initial share of 2G ethanol (e.g. 1.5% or 3.6%, following the Renewable Energy Directive (RED II)) influence the real demand of 2G ethanol?

**Figure 5:** Partial established production scenario for 2G ethanol demand



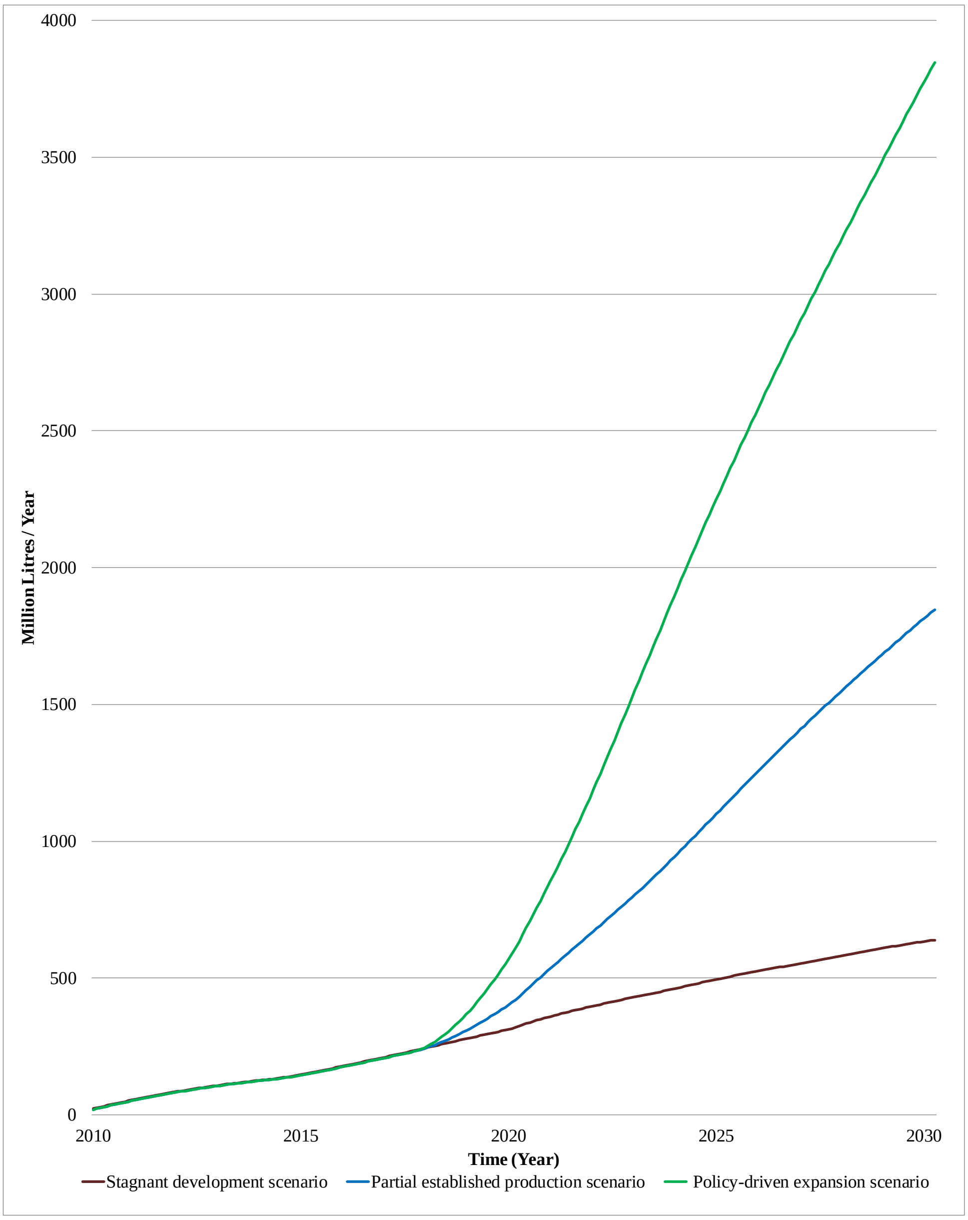

As expected, the figures show that the learning effects have a stronger impact on the overall demand, if the initial share of 2G in total fuel consumption is increasing. Figure 5 shows the run for an initial share of 1.5% and the figure 6 for 3.6%, and represent thereby the partial established production scenario and the policy driven expansion scenario for 2G ethanol demand.

**Figure 6:** Policy driven expansion scenario for 2G ethanol demand



As the diagrams show, the higher the initial share of 2G ethanol, the faster the gap between the policy-driven demand and the overall demand is growing. This derives due to a lower price level, leading to additional demand beyond the policy-driven demand. While the gap holds a value of 100 million litres for an initial share of 0.5%, it is 350 million litres for 1.5%, and approximately 850 million litres for 3.6%. Finally, figure 7 summarises varying developments in demand for 2G ethanol based on scenarios with different assumptions.

**Figure 7:** Dynamics of demand for 2G ethanol by stagnant development scenario, partial established production scenario and policy-driven expansion scenario



## 2.4 Conclusions

A key approach to progress along the path to further sustainable development is the continuous switch to second-generation biofuels, which are derived from non-food resources. One of the most promising biofuels is lignocellulosic ethanol. Nevertheless, due to the current absence of cost competiveness, the 2G ethanol market is strongly dependent on policy support. Moreover, the production costs for 2G ethanol play a crucial role for future cost competitiveness and thereby for market development. Hence, the key question that arises is how the linkage between the policy-induced market growth and the reduction of production costs can influence the dynamics for 2G ethanol demand.

This chapter takes the first step towards analysing the interactive effects of policy incentives and learning effects on 2G ethanol demand. Therefore a System Dynamics model was firstly developed, which reproduces the system structure in a very simplified way, but is able to provide initial insights into the system's behaviour. By means of simulated tests, it was possible to develop the first hypothesis about the dynamics of 2G ethanol demand. Through the simulations, we can show that the learning effects influence positively the reduction of process costs and the 2G ethanol market price, thereby influencing the 2G demand positively. This effect is enhanced by reinforcing policy incentives in terms of indicative targets (Renewable Energy Directive (RED II)).

# 3 System Dynamics modelling of the European demand for bio-based plastics

## 3.1 Introduction

Bio-based plastics (bio-based polymers) represent an important segment of bio-economy. The term bio-based plastic refers to the raw material used (biomass instead of fossil fuels), or to production methods (biotechnology instead of chemical synthesis) or to bio-degradability (Kaeb & General 2009; Philp 2014; Shen et al. 2009). We refer to biotechnology-produced plastics based on biomass.

Bio-based plastics (BP) are used in a wide range of applications (e.g. packaging, textiles, consumer goods, agriculture & horticulture, automotive & transport) and provide potential for mitigating climate change by lowering $CO_2$ emissions (Mapleston 2006). However, for most bio-based products and applications the costs are twofold or even higher compared to fossil-based alternatives (Iles & Martin 2013; van den Oever et al. 2017). Despite the considerable technological progress (Bastioli 2005; Shen et al. 2009; van den Oever et al. 2017) this gap has not been closed yet (van den Oever et al. 2017). Moreover, the decrease in oil prices has even diminished their cost competiveness, because the competing fossil-based plastics thereby became cheaper on the market.

In the last 5-10 years, various policy instruments for supporting the competitiveness of bio-based plastics on the market have been discussed (Bio-Tic 2015; Kaeb & General 2009; Philp 2014). The propositions range from bans for fossil-based plastics to exemption from value-added tax, grants for commercial plants, standardization and labelling (Bio-Tic 2015). Such measures may support the uptake of bio-based plastics and lead to high cost competiveness in the long-term.

Although we know from the literature that production scale size and technological progress can reduce market price via production costs (Festel et al. 2014) and that policy incentives may reinforce this effect (Philp 2014), we do know much about their interlinked effect on the competitiveness of the bio-based plastics on the market. Furthermore, we do not know in any detail how the changing prices of oil, as a basis for fossil-based plastics (alternative products on the market), influences the competitive situation on the market. Hence, we led the focus of this study on the research questions:

- *How does the linkage between the reduction of production costs (resulting from scaling and learning effects) and the changed framework conditions (resulting from policy incentives and oil price dynamics) influence the competitiveness of bio-based plastics on the market?*
- *What are the effects of the scenarios elaborated in the PROGRESS CSA on bio-based plastics?*

To answer these questions we constructed a System Dynamics model for the value chain of bio-based plastics. Our model contains only those segments where bio-based plastics compete mostly directly as a drop-in for certain applications and can be approximated by the relative costs between the fossil-based and bio-based alternatives. Cost structures, current market figures and potential learning rates have been based on current literature (Daugaard et al. 2015; European Bioplastics 2017; Festel et al. 2014; Shen et al. 2009; Tsiropoulos 2016; van den Oever et al. 2017; Wydra 2010). Therefore, cost data for bio-based plastics has been used and compared to those fossil-based plastics for which bio-based is mainly used as a direct substitute.

## 3.2 Model conceptualisation

To develop a system structure which links scaling and learning effects resulting from production capacities with the effects of the price competition on demand for bio-based plastics, we built a simulation model with three subsystems:

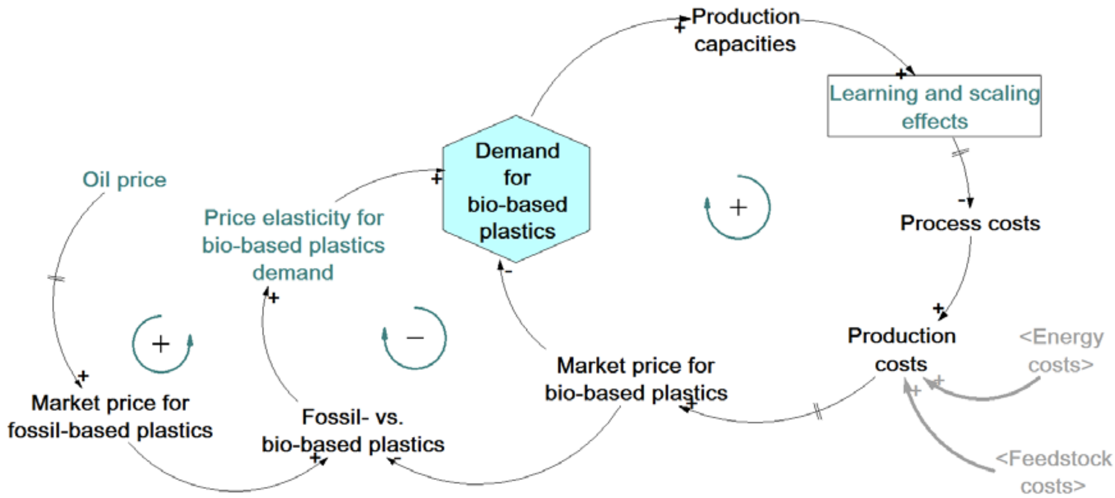
1. Learning and scaling effects on production costs
2. Effect of the oil price on the price of fossil-based plastics
3. Effect of the price for bio-based plastics on demand

### 3.2.1 Causal loop diagram of demand for bio-based plastics

We started our modelling with the assumption that a multiplication of the production capacities reduces the process costs having thereby a lowering effect on the market price for bio-based plastics (Iles & Martin 2013; van den Oever et al. 2017; Wydra 2010). Dynamic scaling and learning effects resulting from production scale size and technological process improvements represent the main reasons therefore (Daugaard et al. 2015; Festel et al. 2014). A quite large amount of literature has studied potential costs reduction from scale and learning effects and assumes significant reductions, which may lead to convergence compared to fossil-based plastics in around 15-20 years (Daugaard et al. 2015;

European Bioplastics 2017; Festel et al. 2014; Shen et al. 2009; Tsiropoulos 2016; van den Oever et al. 2017; Wydra 2010). Finally, via higher price elasticity it leads to a positive feedback loop within the subsystem which explains the positive influence of learning and scaling effects on demand for bio-based plastics.

**Figure 9:** Causal loop diagram



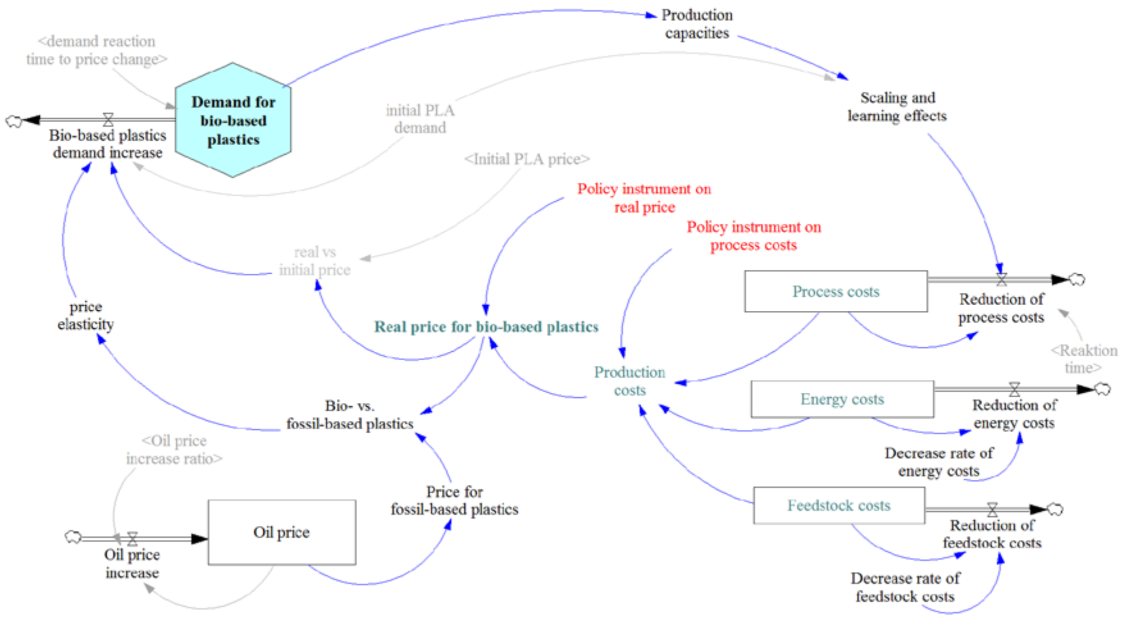

To simplify our System Dynamics model, we assume production costs as a sum of process costs, energy costs and feedstock costs. With the same reason, we calculate production costs as an individual variable of the market price for the bio-based plastics, neglecting thereby e.g. R&D costs, distribution costs etc.

The market price of bio-based plastics operates in competition with the market price of fossil-based plastics as their non-bio-based alternative (Bio-Tic 2015; Kaeb & General 2009; Iles & Martin 2013; McCormick & Kautto 2013). The price of fossil-based plastics depends directly on the oil price on the market. Because of this interrelatedness, the price elasticity for bio-based plastics is in conjunction with the price of the fossil-based plastics. Namely, it will be higher in case the bio-based plastics are cheaper in contrast to fossil-based plastics and lower in case they are more expensive on the market – building thereby a negative feedback loop. From the perspective of oil price, the higher the oil price, the higher the price for fossil-based plastic and thus the higher the demand for bio-based plastics – building thereby a positive feedback loop (Bio-Tic 2015; European Bioplastics 2017; van den Oever et al. 2017).

### 3.2.2 Stock and flow diagram of demand for bio-based plastics

Based on the conceptual models of two above presented subsystems (causal loop diagrams) we build a simulation model on the VENSIM software platform (see figure 10).

**Figure 10:** Stock and flow diagram for bio-based plastics demand




As the starting point for the modelling we use the initial demand for bio-based plastics and reflect it on production capacities under the assumption:

$$Q^{BP}(t) = PR^{BP}(t) \tag{2.1}$$

where:

| | | |
|---|---|---|
| $PR^{BP}(t)$ | Monthly Production capacity | *[million kg/month]* |

For modelling process costs we use scaling and learning effects whose level is based on the monthly production capacities, as explained in the first conceptual model.

For calculating monthly process costs we used the model:

$$C^{BP}_{process}(t) = C^{BP}_{process}(t_0) + \int_{t_0}^{t_{180}} \left(C^{BP}_{process}(t) * LS(t)\right) dt \tag{2.2}$$

where:

| | | |
|---|---|---|
| $C^{BP}_{process}(t)$ | Process costs | *[EUR/kg]* |
| $LS(t)$ | Learning and scaling effects on process costs | *[Dmnl]* |

For modelling the influence of production capacities on process costs, we calculate on scaling and learning effects from 2% to 0.5% in accordance with the multiplication of the production capacities compared to the start demand - from 1 time to 4 times (Daugaard et al 2015; Festel et al. 2014). In accordance with the current literature (Daugaard et al. 2015; European Bioplastics 2017; Festel et al. 2014; Shen et al. 2009; Tsiropoulos 2016; van den Oever et al. 2017; Wydra 2010) we use higher scale effects (2%) for multiplications up to 1 times and reduce them with the increase of production capacities to 0.5% for a multiplication of 4 times. A delay of 3 months is also integrated into the model, which indicates the time for real reduction of prices after a scale and/or learning effect occurs.

Production costs:

$$C^{BP}_{production}(t) = C^{BP}_{feedstock}(t) + C^{BP}_{energy}(t) + C^{BP}_{process}(t) \tag{2.3}$$

where:

| | | |
|---|---|---|
| $C^{BP}_{production}(t)$ | Production costs | *[EUR/kg]* |
| $C^{BP}_{energy}(t)$ | Energy costs | *[EUR/kg]* |
| $C^{BP}_{feedstock}(t)$ | Feedstock costs | *[EUR/kg]* |

Based on the causal linkages of the conceptual model (See figure 10) we calculated monthly demand for bio-based plastics as:

$$Q^{BP}(t) = Q^{BP}(t_0) + \int_{t_0}^{t_{180}} \left(Q^{BP}(t_0) * P_{\Delta}(t) * e_p^{BP}(t)\right) dt \qquad (2.4)$$

$$P_{\Delta}^{BP}(t) = 1 - \frac{\left(P_{real}^{BP}(t)\right)}{\left(P^{BP}(t_0)\right)} \qquad (2.5)$$

where:

| | | |
|---|---|---|
| $Q^{BP}(t)$ | Monthly demand for bio-based plastics | *[million kg/month]* |
| $Q^{BP}(t_0)$ | Initial demand for bio-based plastics | *[million kg/ $t_0$]* |
| $P_{real}^{BP}(t)$ | (real) market price for bio-based plastics | *[EUR/kg]* |
| $P^{BP}(t_0)$ | Initial price for bio-based plastics | *[EUR/kg]* |
| $P_{\Delta}^{BP}(t)$ | Difference between market price and initial price | *[Dmnl]* |
| $e_p^{BP}(t)$ | Price elasticity for bio-based plastics | *[Dmnl]* |

As the customers do not simultaneously react to price changes, a reaction time to price change as delay of two months is integrated in the model as well.

## 3.3 Results of simulation

After validation tests of our System Dynamics model, in which we verified the structure of the model and validated it through extreme conditions experiments and sensitivity tests, the model was ready for the first system behaviour analysis for policy making. For a dynamic analysis and a deeper understanding of the system's behaviour, we conducted various simulation runs and tests. Some exemplary runs are shown in the following and interpreted to generate the first dynamic hypotheses.

In order to gain a deeper insight into the price competitiveness and the dynamic demand for the bio-based plastics, we ran various model simulations based on different assumptions for the future oil price and policy incentives, mostly based on the qualitative scenarios elaborated in the PROGRESS project:[5]. For oil prices, we used different assumptions

[5] See Deliverable 4.1 on www.progress-bio.eu. In difference to the qualitative scenarios a baseline scenario was simulated here.

based on IEA scenario projections (IEA 2016). For policy incentives, we calculated tax exemptions as price lowering effects and direct subsidies for new technologies in production as process costs lowering effects. For analysing the effects of price competition we calculated lower price elasticity in the situation that bio-based plastics are more expensive than fossil-based plastics, and higher elasticity in the opposite situation. This assumption reflects the pattern that some consumer segment will start to consume bio-based plastics only if they are less expensive than fossil-based ones. Based on the current literature, we calculated 1,000 tons per year for initial demand of bio-based plastics in Europe. To summarize the following scenarios have been modelled (see also table 3)

**Baseline scenario:**

Incremental advances in technology and market awareness as well as no policy changes were assumed.

**High oil price scenario:**

A steady rise of oil prices to 127 US dollars per barrel in 2030 was assumed, together with no significant policy measures.

**De-risking scenario:**

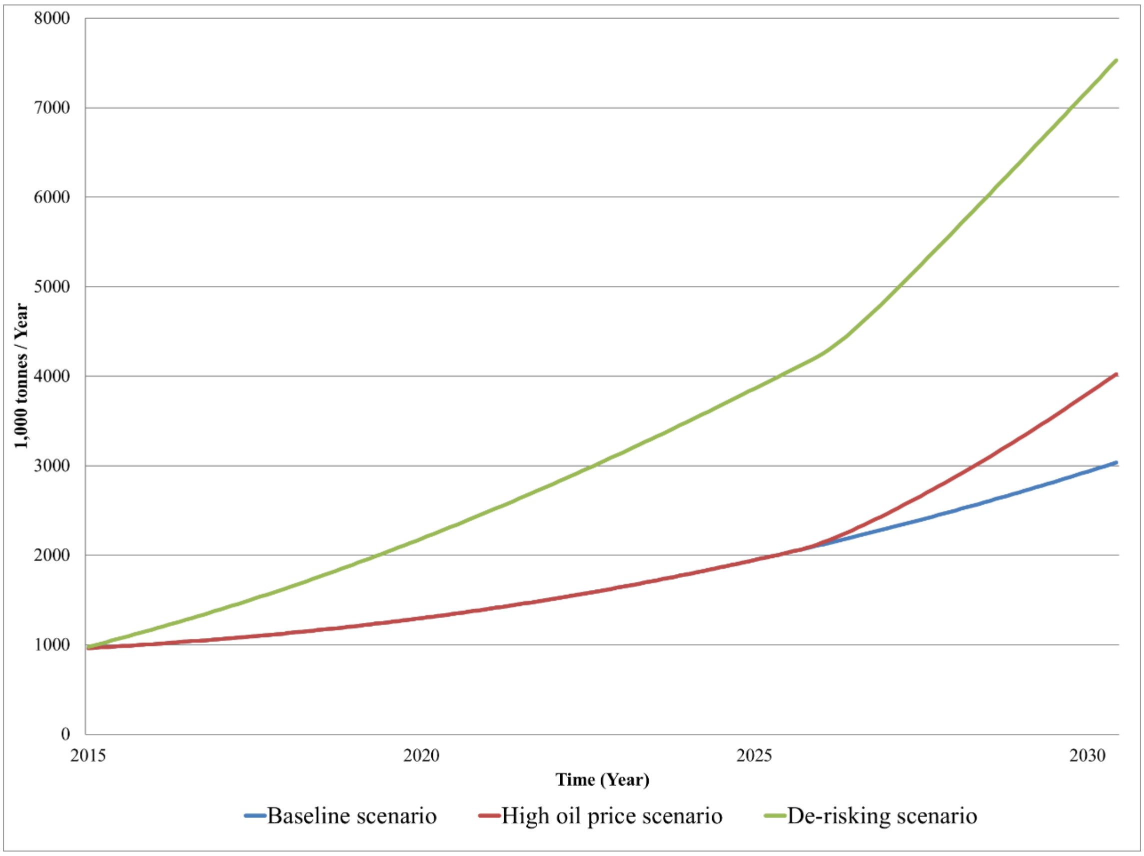
Substantial policy support for commercial activities, tax exemptions as price lowering effects as well as a higher demand by consumers were assumed.

**Table 3:** Assumptions for scenarios

| Scenarios | Oil price (US$/bbl ) | Policy incentives | | Price elasticity | |
|---|---|---|---|---|---|
| | | Policy instrument on real price | Policy instrument on process costs | Bio-based > Fosill-based | Bio-based < Fosill-based |
| Baseline scenario | ~100 | no | no | 0.3 | 0.6 |
| High oil price scenario | ~127 | no | no | 0.3 | 0.6 |
| De-risking scenario | ~100 | yes | yes | 0.4 | 0.7 |

Figure 11 depicts three scenarios of dynamics of the demand for bio-based plastics resulting from the effects of scaling and learning effects on market price as well as on competitive market situation of bio-based with fossil-based plastics.

**Figure 11:** Dynamics of demand for bio-based plastics by low and high oil prices as well as by the influence of policy measures

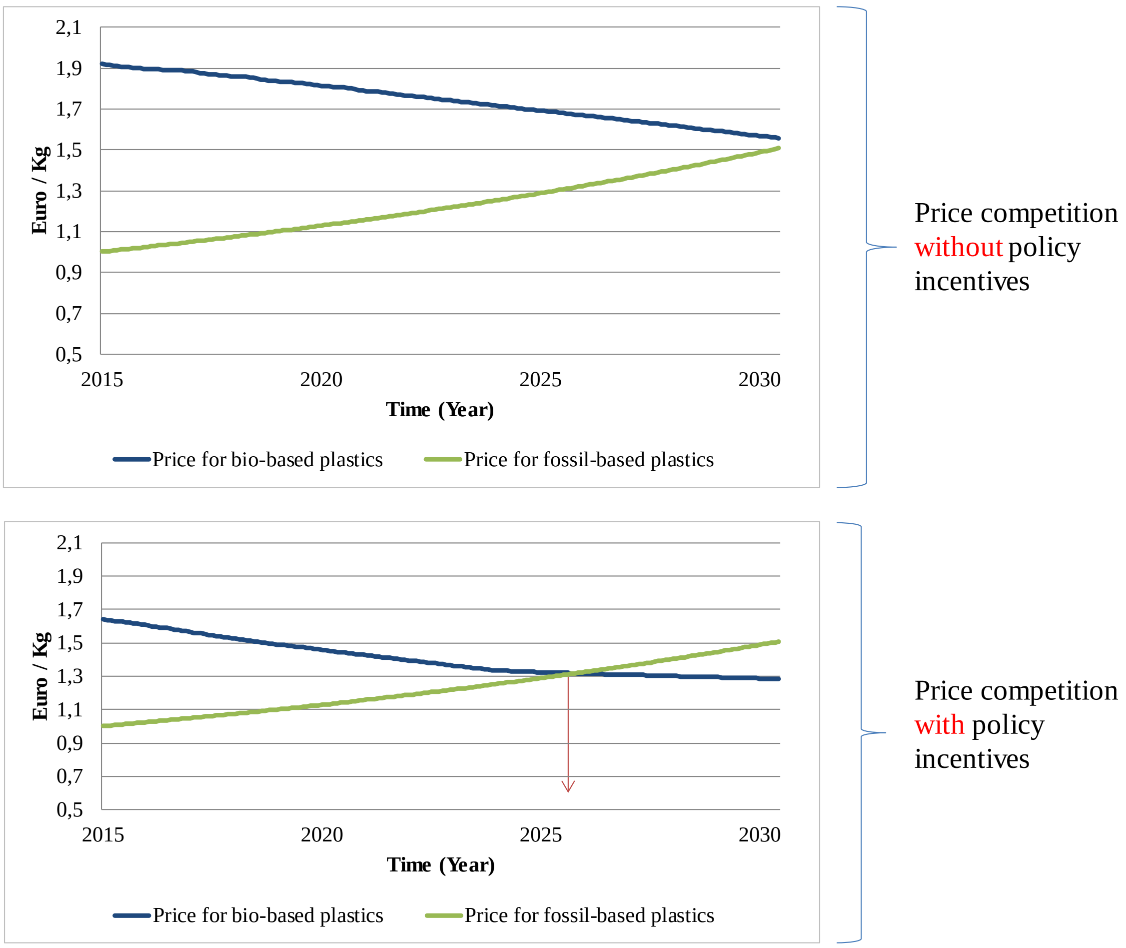



The **baseline scenario** presented with the blue line in the figure 11 depicts the development of demand for bio-based plastics at modest rising oil price and thereby lower prices of fossil-based plastics on the market. In this scenario, no policy incentives are calculated. In such a case, the slow reduction of process costs of production is based only on incremental advances in technology leading to a lower increase in process efficiency and thereby to limited learning and scaling effects. Hence, the price for the bio-based plastics does not achieve the competitiveness in the considered time period (see Figure 12).

The second scenario represents the **high oil price scenario** that assumes a steady rise of the oil price to 127 US$/bbl in 2030 (IEA 2016). To analyze only the effects of higher oil price on demand of bio-based plastics, we took the same assumptions of the base run and increased the oil price ratio only. As the red line in the figure 11 shows, the higher price for fossil-based plastics has only a modest effect on market demand. Hence, it still takes some years till the cost competiveness to fossil-based products is achieved. The results show also that only when the tipping point of price competiveness is reached, the demand for bio-based plastics will significantly take up.

In the third **"de-risking" scenario** we assumed modest rising oil price and integrated policy support for commercial activities into the simulation analysis. Moreover, we used higher market response of consumers operationalised with higher price elasticity, in contrast to the previous scenarios, for calculating demand for bio-based plastics in competition with the fossil-based plastics. The results (see the green line in the figure 11) show a much stronger growth of demand for bio-based plastic in comparison to the other scenarios despite the low oil price on the market. This result shows that stronger policy incentives in the form of tax exemptions with price lowering effects as well as subsidies for new technologies with process costs' lowering effect can reinforce the effects that production scale size and technological process improvements have on the competitiveness of bio-based in comparison to fossil-based plastics (see figure 12).

**Figure 12:** Price competition between the bio-based and fossil-based plastics with and without policy incentives



## 3.4 Conclusions

Bio-based plastics are used as raw materials in a wide range of applications and provide potential for mitigating climate change by lowering $CO_2$ emissions. However, because of the high production costs compared to fossil-based alternative products, they are currently not cost competitive on the market. Moreover, the decrease of oil price as main antecedent of fossil-based plastics has even been diminishing their competiveness. Thus, the future of bio-based plastics on the market depends on the changing framework conditions, in the form of policy supports and increase in oil price. The key question that arises, in this regard, is how the linkage between the reduction of production costs and the changed framework conditions influences the competitiveness of bio-based plastics on the European market in the next 15 years period.

This chapter takes the first step towards analyzing how the linkage between the reduction of production costs (resulting from scaling and learning effects) and the changed framework conditions (resulting from policy incentives and oil price dynamics) influences the competitiveness of bio-based plastics on the market. Therefore a first System Dynamics model was developed, which reproduces the system structure in a very simplified way, but is able to provide first insights into the system's behaviour.

Based on our analysis it was possible to develop the first hypothesis about the dynamics of the demand for bio-based plastics. By means of our simulations we can show that the scaling and learning effects - resulting from build up and running of new production capacities as well as adopting new technologies - influence positively the reduction of process costs and the bio-based plastics price on market, thereby influencing the demand positively. However, these effects alone are not sufficient for achieving cost competitiveness of the bio-based plastics on the European market. Thus, the framework conditions in the form of increasing price of oil as main antecedents of the fossil-based plastics, but especially policy incentives would play a crucial role for improving the dynamics of the demand for bio-based plastics within a significantly shorter period of time.

# 4 References


Barisa A., Romagnoli F., Blumberga A., Blumberga D. (2015): Future biodiesel policy designs and consumption patterns in Latvia: a system dynamics model. In: Journal of Cleaner Production 88, p. 71–82.

Bastioli C. (2005): Handbook of biodegradable polymers. iSmithers Rapra Publishing.

Bio-Tic (2015): Overcoming hurdles for innovation in industrial biotechnology in Europe - BIO-TIC Market Roadmap.

Daugaard T., Mutti L., Wright M., Brown R., Componation P. (2015): Learning rates and their impacts on the optimal capacities and production costs of biorefineries. In: Biofuels, Bioproducts and Biorefining 9(1), p. 82-94.

Daugaard T., Mutti L., Wright M., Brown R., Componation P. (2015): Learning rates and their impacts on the optimal capacities and production costs of biorefineries. In: Biofuels, Bioproducts and Biorefining 9(1), p. 82-94.

De Wit M., Junginger H.M., Lensink S., Londo M., Faaij A. (2010): Competition between biofuels: Modeling technological learning and cost reductions over time. In: Biomass and bioenergy 34(2), p. 203-217.

Dörner D. (1989): Die Logik des Misslingens. Strategisches Denken in komplexen Situationen. 1st ed., Hamburg.

EC (European Commission) (2016): Proposal for a directive of the European Parliament and the Council of Europe on the promotion of the use of energy from renewable sources (recast); https://ec.europa.eu/energy/sites/ener/files/documents/1_en_act_part1_v7_1.pdf

ePURE (2015): European renewable Ethanol – Enabling Innovation and Sustainable Development. State of the Industry 2015. Brussels.

European Bioplastics (2017): Bioplastics market data. http://www.european-bioplastics.org/market/, assessed on 4th June 2017.

Festel G., Würmseher M., Rammer C. (2014): Scaling and learning effects of biofuels conversion technologies. In: Energy Technology 2(7), p. 612-617.

Festel G., Würmseher M., Rammer C., Boles E., Bellof M. (2014): Modelling production cost scenarios for biofuels and fossil fuels in Europe. In: Journal of Cleaner Production 66, p. 242-253.

Ford DN, Sterman JD. (1998): Dynamic modeling of product development processes. System Dynamics Review 14(1): p. 31–68.

Forrester J. W. (1968): Industrial Dynamics - After the first Decade. In: Management Science Vol. 14, p. 398–415.

Forrester J. W. (1971): World Dynamics.

Hirschnitz-Garber M., Gosens J. (2015): Producing bio-ethanol from residues and wastes - A technology with enormous potential in need of further research and development. Policy Brief No. 2, November 2015. Sweden.

IEA (International Energy Agency) (2016): World energy outlook 2016. Paris.

IEA-ESTAP, IRENA (2013): Production of Liquid Biofuels, Technology Brief.

Iles A., Martin A.N. (2013): Expanding bioplastics production: sustainable business innovation in the chemical industry. In: Journal of Cleaner Production 45, p. 38-49.

Jonker J. G. G., Van Der Hilst F., Junginger H. M., Cavalett O., Chagas M. F., Faaij A. P. C. (2015): Outlook for ethanol production costs in Brazil up to 2030, for different biomass crops and industrial technologies. In: Applied Energy 147, p. 593-610.

Kaeb H., General S. (2009): Bioplastics: Technology, Markets, Policies. In: 4th European Bioplastics Conference, Berlin (Vol. 4, pp. 10-11).

Larsen, E. R., & Bunn, D. W. (1999): Deregulation in electricity: understanding strategic and regulatory risk. Journal of the Operational Research Society, 50(4), p. 337-344.

Mapleston P. (2006): Environmentally degrading: Bioplastics in Europe (part 2). In: Plastics Engineering Europe Spring, p. 24-29.

McCormick K., Kautto N. (2013): The bioeconomy in Europe: An overview. In: Sustainability 5(6), p. 2589-2608.

Milling P. (1984): Leitmotive des System-Dynamics-Ansatzes. In: Wirtschaftswissenschaftliches Studium Vol. 13, p. 507–513.

Milling P. (2002): Entscheiden in komplexen Systemen. Berlin.

OECD, FAO (2016): OECD-FAO Agricultural Outlook 2016-2025. OECD Publishing. Paris.

Paich M. (1993): Boom, Bust, and Failures to Learn in Experimental Markets. In: Management Science Vol. 1993.

Philp J. C. (2014): Biobased chemicals and bioplastics: Finding the right policy balance. In: Industrial Biotechnology 10(6), p. 379-383.

Phillips S., Flach B., Lieberz S., Rondon M., Williams B., Wilson C. (2016): EU Biofuels Annual 2016. http://www.fas.usda.gov/data/eu-28-eu-biofuels-annual-0

Sandrock, J. (2007): System dynamics in der strategischen Planung: zur Gestaltung von Geschäftsmodellen im E-Learning. Springer-Verlag.

Schröter, M. (2006): Strategisches Ersatzteilmanagement in Closed-Loop Supply Chains. Deutscher Universitäts-Verlag, Wiesbaden.

Shen L., Haufe J., Patel M.K. (2009): Product overview and market projection of emerging bio-based plastics PRO-BIP 2009. Report for European polysaccharide network of excellence (EPNOE) and European bioplastics.

Sterman J. D. (1989): Modelling Managerial Behaviour: Misperceptions of Feedback in a Dynamic Decision Making Experiment. In: Management Science Vol. 35, p. 321–339.

Sterman J. D. (2000): Business dynamics: systems thinking and modeling for a complex world.

Sterman J. D. (2001): System Dynamics Modelling: TOOLS FOR LEARNING IN A COMPLEX WORLD. In: California Management Review Vol. 43.

Stumpfe J. (2002): Simulation zur Entscheidungsunterstützung im Innovationsprozess industrieller Unternehmen. In: Systemdenken und Virtualisierung: Unternehmensstrategien zur Vitalisierung und Virtualisierung auf der Grundlage von Systemtheorie und Kybernetik, p. 173–180.

Timilsina G., Shrestha A. (2010): Biofuels: markets, targets and impacts. The World Bank Working Paper 5364.

Tsiropoulos I. (2016): Emerging bioeconomy: Assessing the implications of advanced bioenergy and biochemicals with bottom-up and top-down modelling approaches. Doctoral dissertation, Utrecht University.

UNCTAD (2015): Second Generation biofuel Markets: State of Play, Trade and Developing Country Perspectives. UNCTAD/DITC/2015/8. Switzerland.

Van den Oever M., Molenveld K., Maarten van der Zee M., Bos H. (2017): Biobased and biodegradable plastics – Facts and Figures.

Vimmerstedt L.J., Bush B., Peterson S. (2012): Ethanol distribution, dispensing, and use: analysis of a portion of the biomass-to-biofuels supply chain using system dynamics. In: PLOS ONE 7 (5), e35082.

Wydra S. (2010): Produktions-und Beschäftigungseffekte neuer Technologien: am Beispiel der Biotechnologie.

Ye F., Paulson N., Khanna M. (2014): Technology uncertainty and learning by doing in the cellulosic biofuel investment. In: Agricultural & Applied Economics Association’s 2014 AAEA Annual Meeting. Anais.