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Biomass based energy intermediates boosting biofuel production

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Deliverable

Book Chapter

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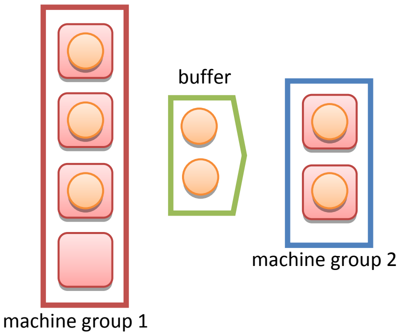
1 Introduction

This chapter summarizes the tasks and results accomplished in work package four (WP4) of the BioBoost project. The main focus of WP4 is optimal logistics for biomass and energy intermediates. We have derived a logistic model for the BioBoost scenarios which encompasses all stages in the value chain, from biomass gathered from the field or forest, to the utilization of the final product and we also performed a risk assessment for the proposed logistic processes. A central topic of WP4 is simulation of the processes to allow analyses on a regional level. A software tool has been developed which optimizes plant locations and capacities as well as logistics based on regional information including feedstock availability, feedstock costs, transport infrastructure, and various cost factors such as labour costs or investment costs, which allows analyses of the most profitable regions for potential implementation and ramp up of the developed technologies.

This chapter is structured as follows. First, we describe the methodology that we used to gather data on logistics and to define the logistic model as well as the concept of simulation-based optimization that we used for finding feasible scenarios for the initial implementation of the developed technologies and the scenarios for the ramp up of the production of next generation bio-fuels in Europe.

2 Methodology

We propose a logistic model for transport and handling of feedstock and energy intermediates using a thorough literature study and interviews with experts. Details on the resulting model are described in detail further below. The logistic model contains cost rates for all possible handling and transport equipment that are subsequently used in a simulation model that also contains essential data gathered in other work packages.



For constructing optimal scenarios for feedstock usage, plant locations and transport networks, we employ a technique called simulation-based optimization [Gos2003]. This technique combines a detailed and accurate simulation of scenarios with sophisticated meta-heuristic algorithms that tune parameters of scenarios.

A simple example for simulation-based optimization is the optimization of the buffer size between machine groups in a production environment. In this example the processing times of machines are known and the optimal size of the buffer between machines has to be determined. By simulating the production process using random operation times, the utilization of the buffer between machines can be determined and it is easy to calculate the total throughput and how often machines are blocked because the buffer is full or empty. Through repeated simulation of the process the expected performance and its distribution can be evaluated for a certain buffer size. The optimization process uses this information to improve the buffer sizes step by step. Usually, when using simulation for the evaluation of scenarios or when scenarios have a certain complexity it is not possible to find the optimal solution analytically or even to calculate optimal steps for iteratively improving the scenario and therefore heuristic approaches (such as simulated annealing [Kirk1983] or evolutionary algorithms [Bäck1996]) or are often used for the optimization.

In the BioBoost project a simulation model describes the full value chain from the feedstock acquisition to the final step of disposal of the produced products and has many predetermined parameters (such as feedstock potentials and transport distances between regions) for which accurate data has been acquired by all partners within the BioBoost project. Additionally, the model has many different parameters (such as plant locations and plant capacities) influencing the efficiency of the scenario for which optimal choices have to be determined. Using specialized meta-heuristics we optimized these parameters. Figure 1 shows the interrelation between the simulation model and the optimization algorithm.

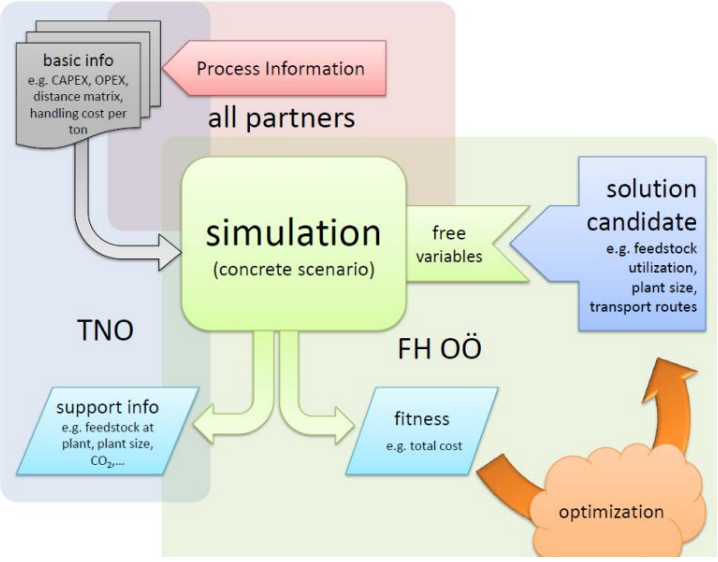


Figure 1: Concept of the cyclic process of simulation-based optimization

3 Logistic Processes

The simulation model requires data for all logistics processes. Therefore, the value chain from the source (which are organic raw materials) to the sink (the final conversion plant that produces the liquid fuel) needs to be represented by individual logistics processes. In BioBoost the logistics processes include the transport, handling and storage of biological raw material and the intermediates from the conversion processes (see Table 1). Logistics has been a focus of research since the 1970s and has attracted many researchers since then who have worked on analysing and improving core logistics processes. Intensified globalization and better tracing technologies have resulted in an increased interest in logistics functions recently. A thorough investigation of the various logistics processes which are relevant in BioBoost yields cost, structural data and performance data, which are necessary for the simulation model. In addition, we also determined CO_2 yields from fossil fuels during transport and handling.

Table 1: Basic logistics processes

Transfer function	Transport	Handling	Storage
Based on	Spatial distribution	Material distribution	Temporal distribution
Demand for transfer function	Divergent locations of value creation (globalized production networks)	Divergent lot sizes in production, inventory, transportation, etc.	Divergent points in time of production and consumption

In BioBoost, the main materials that are manipulated along the supply chain are biomass residues (from the various feedstock types) and energy carriers (materials which are created in de-centralized plants). These two types of material (biomass residues and energy carriers) differ significantly in their characteristics and thus require separate treatment with respect to logistics processes. Figure 2 shows logistics for biomass residues and energy carries along the BioBoost value chain as well as the system boundary that was considered in the analysis of the logistics processes.

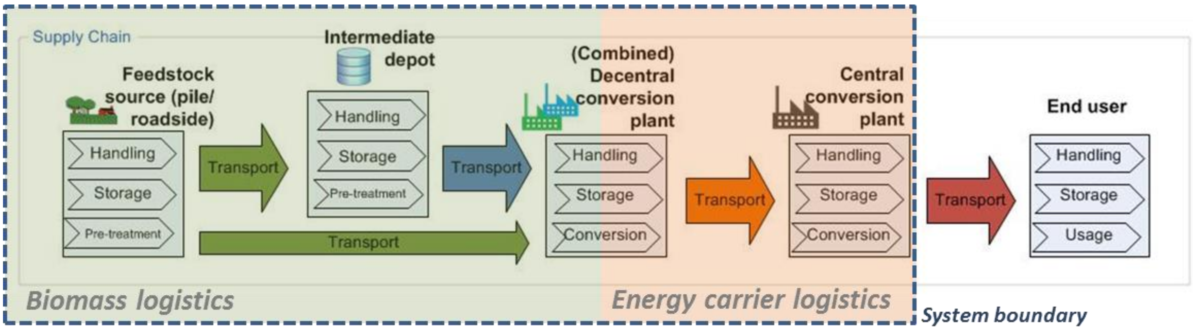


Figure 2: Overall system boundary

The BioBoost logistics model involves five echelons: feedstock sources (pile, roadside), intermediate depots, decentral conversion plants, central conversion plants, and end users. The logistics for delivery to end users has not been included in the model as we assume that logistics infrastructure for this echelon is already in place. Therefore, the boundary for the logistics model ends at the central conversion plant.

The challenge in BioBoost lies in defining a supply network that is both environmentally friendly (inducing a low CO_2 footprint) and economically feasible (generating low costs) compared to the cost of fuels or power from fossil sources.

3.1 Reference Pathways and Supply Chain for Biomass Logistics

We assume that the processes of farming, harvesting or bale production are part of farmers' core business and already included in the product price. We also assume that the products (such as straw bales or forestry residue bundles) are available from piles or from storage at the roadside. Pickup from roadside is the start for the BioBoost logistics model. As shown in Figure 3 processes specific to biomass logistics end at decentral conversion plants (DCP) and the full supply chain has either two or three echelons. The logistics model includes the option to add an intermediate depot in-between the sourcing location and the decentral conversion plant. This could be feasible in cases where distances between sourcing regions and the conversion plants are relatively long. The feasibility of an intermediate depot depends on various factors, which will be described on the following pages. Each echelon contains storage and handling processes (loading and unloading), while transport occurs between echelons.

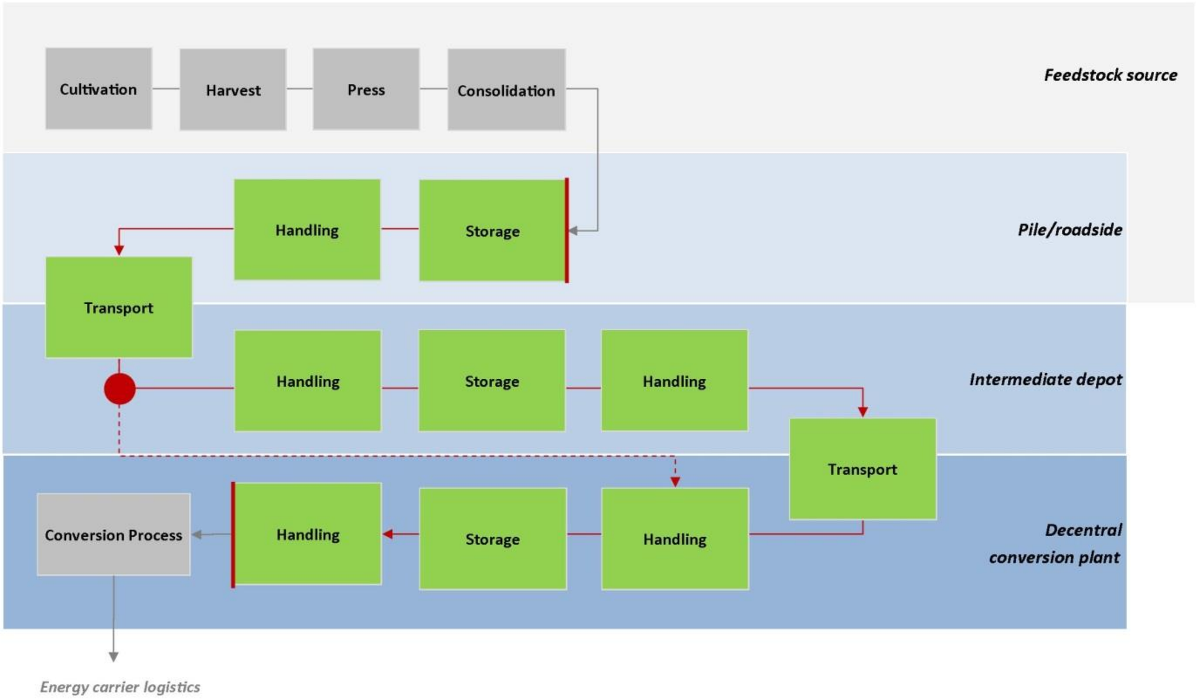


Figure 3: Flow chart showing the steps for the BioBoost logistics model.

In BioBoost multiple different biogenic raw material types are considered as potential feedstock for conversion with specific technologies. The tree conversion technologies are shown in Table 2. As the same raw material could be used e.g. for FP and CP we have considered reference pathways in the logistics model. The reference feedstock type for each conversion technology is also shown in Table 2.

Table 2: Reference feedstock types for each conversion technology

Conversion technology	Reference feedstock type
Fast pyrolysis (FP)	Wheat straw
Catalytic pyrolysis (CP)	Wood chips from logging residues
Hydrothermal carbonization (HTC)	Organic municipal waste

Logistics of biomass – particularly transportation and storage – is significantly affected by the moisture content (MC) which may vary considerably for different feedstock types and is also dependent on e.g. geography and weather conditions. For reasons of easier comparison between processes all cost calculations for the logistics model are therefore based on the dry matter (DM) content. Storage of biomass also leads to dry matter losses due to biological degradation and may eventually render material unusable unless appropriate technical solutions are taken into account. This is relevant in the design phase of logistics processes and has been handled by adapting cost parameters accordingly. Therefore, dry matter losses as well as average storage duration need to be defined for each feedstock type.

Apart from MC and dry matter losses, the bulk density (BD) is another key figure in biomass logistics and has a direct influence on required transport volume. As an example, transporting square bales of straw instead of pure material can substantially increase BD and consequently lower costs. BD is measured as the ratio between weight and volume in kg per m^3. Generally, transport of biogenic feedstock types with a low bulk density is limited by volume, whereas high density feedstock types reach typical payload restrictions. In general, the bulk density of biomass is influenced mainly by (i) moisture content, (ii) type of biomass and (iii) particle size.

3.1.1. Raw materials considered in the logistics pathways

In the BioBoost reference pathways straw is considered as the feedstock type for fast pyrolysis and is provided in square bales only, which measure 2.4 x 1.2 x 0.9 m (length x width x height) and have a weight of 500 kg fresh mass (FM). 500 kg FM equal a bulk density of 193 kg/m³ (MC: 14 wt%), which can be converted to 166 kg/m³ DM for easier comparison. The square bales are stored at roadside on the field and covered to protect them against environmental impacts.

The reference feedstock type for catalytic pyrolysis (CP) is wood chips from logging residues. CP is particularly sensitive to moisture and requires a strict maximum level of acceptable moisture content (<10%). Furthermore, the maximum particle size needs to be below 5 mm; therefore, pretreatment of feedstock is necessary. In general, residues from full tree logging operations show a rather low bulk density (BD) as well as high moisture content (MC), which significantly depends on environmental conditions. Logging residues are mostly stored along roadsides close to forests as piles. At the so-called “green state”, logging residues have a MC between 55 wt% (Scots pine) and 45 wt% (Norway spruce). To prepare them for further processing mobile chippers are used, which produce small wood chips that meet the particle size requirements. So, a much higher bulk density of approximately 276 kg/m³ (MC 30 wt%) can be achieved (equals 193 kg/m³ DM), which allows more efficient transport. A drawback of woodchips is the danger of self-ignition in storage – an issue, which deserves separate examination in the chapter of risk assessments.

Hydrothermal carbonization (HTC) requires organic municipal waste as raw material. In comparison to CP and FP, the moisture content is not an issue with this conversion technology. However, problems may arise because of impurities, e.g. glass, metal or other non-biological debris. Pre-treatment can diminish the risk for this and is included in the cost models. Organic waste is already collected nowadays in municipalities before it is incinerated or composed. For the logistics model we assume that this collection infrastructure is already in place, which is why the collection process has not been considered in the logistics model. Since HTC plants can be operated efficiently at smaller scales than FP and CP plants, they can also be located close to existing organic waste collection places. Hence, we assume that the whole logistics of collection processes already exists and organic waste can – at no additional cost – be redirected to the HTC plant. HTC reactors are then automatically supplied through screw-conveyors. To sum up, no logistics processes like storing, transporting and handling of material need have been examined for biomass logistics of organic municipal waste (material source for HTC).

3.1.2. Infrastructure and assets for the logistics processes

In general, the combination of the product and loading device is defined as a loading unit in logistics. For instance, a roll-off container loaded with wood chips represents a loading unit, which is the most popular loading device for wood chips. A loading device is mainly characterized by its dimensions (meters), payload (tons) and cargo space (cubic meters). Generally, transports contribute significantly to overall logistics costs and should be limited whenever possible.

Tractor trucks are rather designed for on-road transport unlike farm tractors, whose prime area of operation are lose grounds. The different properties of these two vehicle types impact logistics costs considerably. Aside of the tractors, the type of trailers also affect total costs of transportation. Low costs in transport can only be achieved by having full truck loads (FTL) whenever possible. A FTL implies optimal usage of cargo space or payload, depending whether space or weight reach their limits first. Regardless of the utilization on the way between the feedstock source and the plant, transports always return empty. This reduces the transport utilization rates substantially and increases costs of biomass logistics.

Handling equipment allows the transfer of moving goods (e.g. transport) to storing goods. Logistics flows are interrupted by any kind of store, and storage should therefore be minimized but can never be eliminated fully. Handling devices are fundamental at the nodes within the designed supply network. These handling assets are characterized by their lifting heights and capacities. The lifting capacity (these are the tons or cubic meters which can be manipulated at once) limits handling performance significantly. Telescopic handlers have comparatively good lifting capacity, but they are expensive. Gantry cranes are a stationary type of handling equipment, which have a high performance rate (ability to load 8-12 square bales at once) and require infrastructure (building, rails, etc.). Investment costs for gantry cranes are significantly higher compared to other handling devices.

Stores are key elements of logistics and are required to compensate for the time span between production and consumption. Each node in the BioBoost supply network could be a potential storage location. In biomass logistics three locations exist where square bales and wood chips (for FP and CP[1]) might be stored: (1) pile/roadside (feedstock source), (2) intermediate depot and (3) decentral conversion plant.

We assume that wheat straw is stored in squared bales, which are then piled close to the fields. Coverage by plastic sheets reduces the risk of remoistening. In most of Europe, bales are mainly produced in late summer and are stored for the rest of the year. This results in an average storage horizon of approximately 6 months. Other than the storage close to the field, wheat straw bales might also be stored in intermediate depots before they are transported to decentral conversion plants. A safety stock of five days at the plant is assumed, a figure which matches existing publications well.

Wood chips are produced from logging residues and stored close to roadside in the vicinity of the forest. However, storing wood chips in piles requires a thorough consideration of related risks which are:

- Dry matter loss through biological and technical processes (risk of loss)
- Self-heating through biological processes (hazard risk)
- Remoistening through uncovered storage (quality risk)
- Odour nuisance (environmental risk)
- Fungi and sporulation (health risk)

A key element to keep risks under control is to assert low moisture content of wood chips, which slows down biological degradation processes. Short storage times[2], covering the pile with protection sheets, and sufficient air access positively influence a risk reduction. Since it is hard to provide these protective measures in nature, wood chips are preferably transported to intermediate depots for storage.

Dry matter losses of organic materials, which are a result of microbiological activities and spillage during handling and storage processes, must be especially considered in logistics processes. Biogenic residues with high moisture content are generally more prone to dry

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[1] HTC does not require any particular storages in biomass logistics as was explained before

[2] not longer than 3 months

matter loss. In addition, dry matter loss is also a function of particle size and increases with decreasing particle size. This effect is related to three major aspects:

- Chopped biomass exhibit an increased area of exposed surfaces on which microbial activity can occur,
- smaller the particle size is causes decreased air flows through piles and, thus, prevents heat dissipation, and
- chipping releases the soluble contents of plant cells providing microbes with nutrients.

From a cost point of view, the additional storage and handling costs for an intermediate depot (3-echelon design in biomass logistics) have to be compared to higher transport costs due to more frequent trips between the raw material source and the plant if no intermediate depot is in use (2-echelon design). In general southern countries might consider avoiding intermediate depots because of the beneficial climate conditions. Additionally, intermediate depots increase supply security for the plant, which should continuously run at optimal load.

3.1.3. Cost Calculations for Biomass Logistics Processes

The previous considerations are the foundation for calculating the cost of all steps of the logistic model.

Transport costs are evaluated for all vehicle-trailer combinations under regard, which are then expressed in EUR/t (DM)*km. Total annual direct costs have been computed for each vehicle-trailer combination with the major cost elements like depreciation, maintenance, fuel, tire wear, labour cost of the driver, insurances, etc. A comparison of the direct costs of various truck and trailer combinations can be found in Table 3.

Table 3: Transport cost rates

	Biomass logistics costs for		
Transport Asset	*Unit* *(tons dry matter)*	Wheat straw	Wood chips
Farm tractor and tippers	*EUR/tkm*	0.58	0.32
Farm tractor and hook lift trailer	*EUR/tkm*		1.11
Farm tractor and platform trailer	*EUR/tkm*	0.28	
Truck and drawbar/hook lift trailer	*EUR/tkm*		0.29
Truck (and drawbar trailer)	*EUR/tkm*	0.15	0.11

Farm tractors and tippers are the prevailing vehicle-trailer combination for biomass transports in Austria. The calculations show that the major cost elements in transport are depreciation, maintenance, labour and fuel, which all together amount to 87 % of total annual direct costs (mean values).

Handling costs have been calculated for four different equipment types and finally yielded hourly cost rates (EUR/h). Cost considerations contain investment costs and operating costs of the equipment. Table 4 provides an overview of all handling cost rates.

Table 4: Handling cost rates

		Biomass logistics costs for		
Transport Asset	*Handling Asset*	*Unit (tons dry matter)*	Wheat straw	Wood chips
Farm tractor and tippers	Front-end loaders (farm tractor)	*EUR/t*	3.66	7.23
Farm tractor and platform trailer		*EUR/t*	3.53	6.97
Truck and drawbar trailer		*EUR/t*	3.06	6.04
Stock transfer		*EUR/t*	2.10	4.14
Farm tractor and tippers	Telescopic handler	*EUR/t*	1.72	2.88
Farm tractor and platform trailer		*EUR/t*	1.63	2.73
Truck and drawbar trailer		*EUR/t*	1.32	2.20
Stock transfer		*EUR/t*	0.68	1.13
Farm tractor and tippers	Gantry crane	*EUR/t*	1.04	4.65
Farm tractor and platform trailer		*EUR/t*	1.01	4.50
Truck and drawbar trailer		*EUR/t*	0.89	3.98
Stock transfer		*EUR/t*	0.65	2.91
Farm tractor and tippers	Forklift truck	*EUR/t*	2.52	7.50
Farm tractor and platform trailer		*EUR/t*	2.39	7.11
Truck and drawbar trailer		*EUR/t*	1.92	5.71
Stock transfer		*EUR/t*	0.96	2.84
Farm tractor and tippers	Tipping (unloading)	*EUR/t*		0.20
Truck and drawbar trailer		*EUR/t*		0.08
Farm tractor and hook lift trailer	Handling roll-off container	*EUR/t*		0.31
Truck and drawbar/hook lift trailer		*EUR/t*		0.26

Lastly, inventory holding costs include cost elements like warehousing, depreciation, insurance, etc. Storage costs (EUR/t DM) are determined for wheat straw (square bales) and for logging residues/wood chips and for each type of storage. Organic municipal waste is not taken into account because HTC plants are assumed to be located right next to waste collection yards. Data on dry matter losses have been taken from different studies.

Each type of storage is assessed according to its total annual fixed costs including (i) depreciation, (ii) interests on investments, (iii) maintenance and (iv) labour. Taking into account the quantity of material which runs through a store per year gives the average storage costs per ton (EUR/t (DM).

Table 5: Storage cost rates

			Feedstock types	
Storage costs	*Storage location*	*Unit (tons dry matter)*	Wheat straw	Logging residues/ wood chips
Pile/roadside landing	1	EUR/t	1.99	1.99
Intermediate depot	2	EUR/t	10.05	6.23
Decentral conversion plant	3	EUR/t	0.63	0.56

Storing raw material along a road does not cause additional costs because we assume that it is already included in the price for the material. The only additional factor are costs for material cover sheets which can be found in the first row of Table 5. Storage costs per ton (DM) shown in Table 5 amounts to 10.05 EUR/t (DM) for wheat straw and 6.23 EUR/t (DM) for wood chips, which are lower due to higher turnover rates per year. Storage costs at the DCP are also low due to high turnover rates.

3.1.4. The decision for implementing an intermediate depot in biomass logistics

Intermediate depots are common in biomass logistics already nowadays. Although intermediate depots initially add costs to the value chain they then allow the employment of truck transport from the depot to the plant, which is significantly cheaper than a farm tractor.

We have made a small case study for fast pyrolysis for analysing when an intermediate depot is beneficial. Required feedstock quantities (t DM/yr) from raw material depend on the characteristics of the value chain. If an intermediate depots is in place the dry matter losses are smaller. So, supply chains with intermediate depots need fewer raw materials than those without in order to have the same amount of feedstock arrive at the plant. Certainly, storage costs with intermediate depots are higher than without. In addition, we assume that 70% of feedstock is transported with farm tractors, the rest with trucks – a relation, which can also be found in literature. However, when intermediate depots are in use, all material from there to the DCP is transported with trucks to exploit cost advantages.

At a certain average travel distance the lower transport costs due to truck usage should over-compensate for the additional costs of an intermediate depot. It can be demonstrated that this break-even point lies at an average travel distance of approximately 80 km. Shorter transports should take the raw material directly to the plant, for longer transports an intermediate depot should be employed.

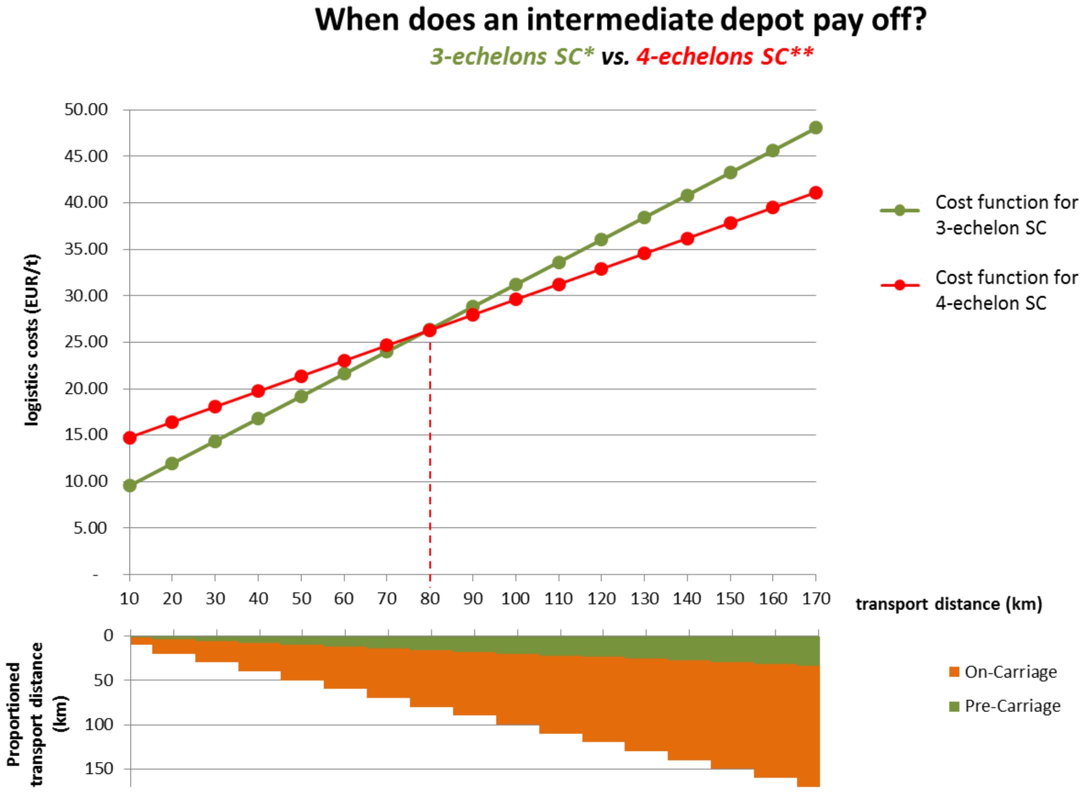


Figure 4: Case study: intermediate depot – 70 % farm tractors, 30 % trucks

3.1.5. Traffic impact assessment (TIA) for conversion plants

Decentral conversion plants need a steady and continuous supply of feedstock. This attracts a lot of additional traffic to the area around the plant. Fast pyrolysis plants should have capacities of appoximately 175.000 t/yr. The number of daily arrivales and departures at the plant can be easily calculated from the maximum vehicle payloads, the capacity of the plant and the number of operating days of the plant. Fast pyrolysis and catalytic pyrolysis plants both require approximately 80 arrivals per day, hydrothermal carbonization plants have smaller capacities and require approximately 8 deliveries a day. According to a recommendation of the Institute of Transportation Engineers (ITE), this amount of arrivals do not require a detailed traffic impact study since the numbers are well below the mentioned limits.

3.1.6. Distributing cost drivers to geographical areas

The logistics cost rates have been calculated for Austria. These costs can be extrapolated to other countries by using official indices from published statistics for the major cost elements, which are:

- Labour costs
- Fuel costs
- Vehicle investment costs
- Construction costs

3.2 Energy carrier logistics as the second part of the biomass value chain

Figure 5 shows the extended model for the whole supply chain. It can easily be seen that energy carrier logistics seems to be simpler than the biomass logistics because there are no intermediate stores between decentral and central conversion plants (CCP).

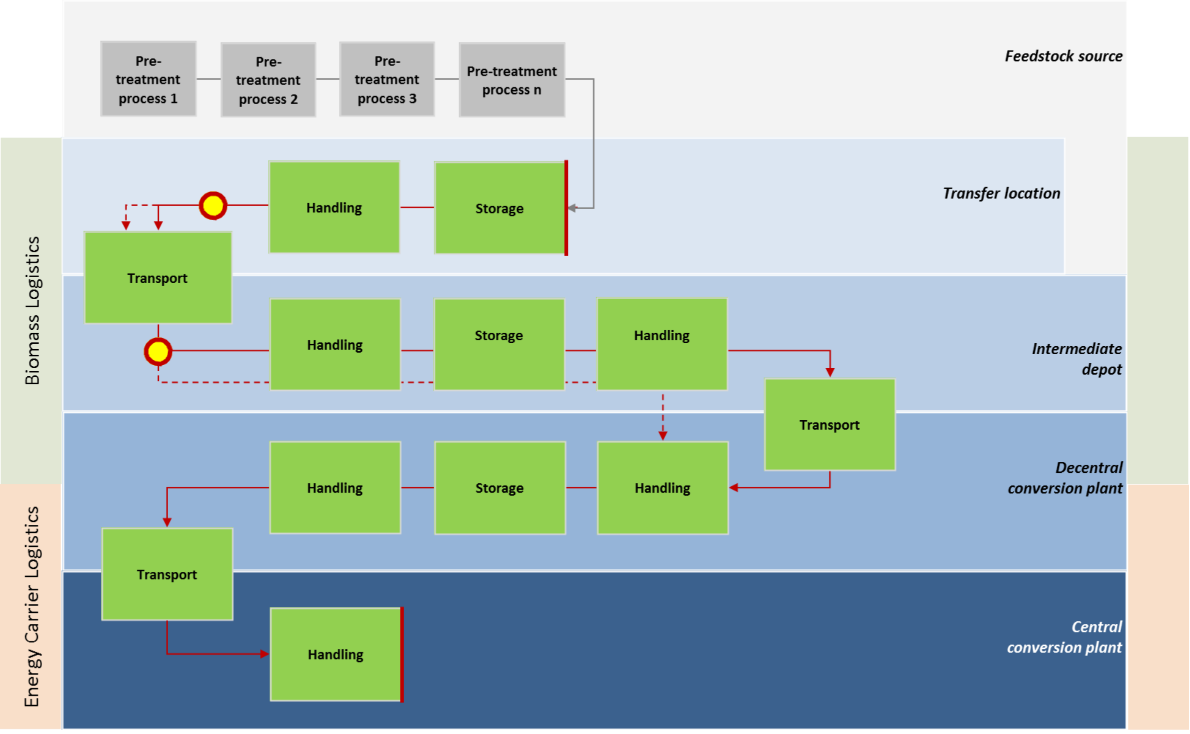


Figure 5: Biomass and energy carrier supply chain in detail

Logistics operations at the plants (DCP and CCP) are not considered since they are already included in the plant infrastructure and need to be designed by the plant designers and operators.

Unlike biomass logistics, which is dominantly based on road transport, rail transport is an option for energy carrier logistics. Rail transportation requires high production quantities which should be delivered directly to a plant. Data on the conversion processes at DCPs have been provided to us by the technology partners in the project and can be found as average data in Table 6.

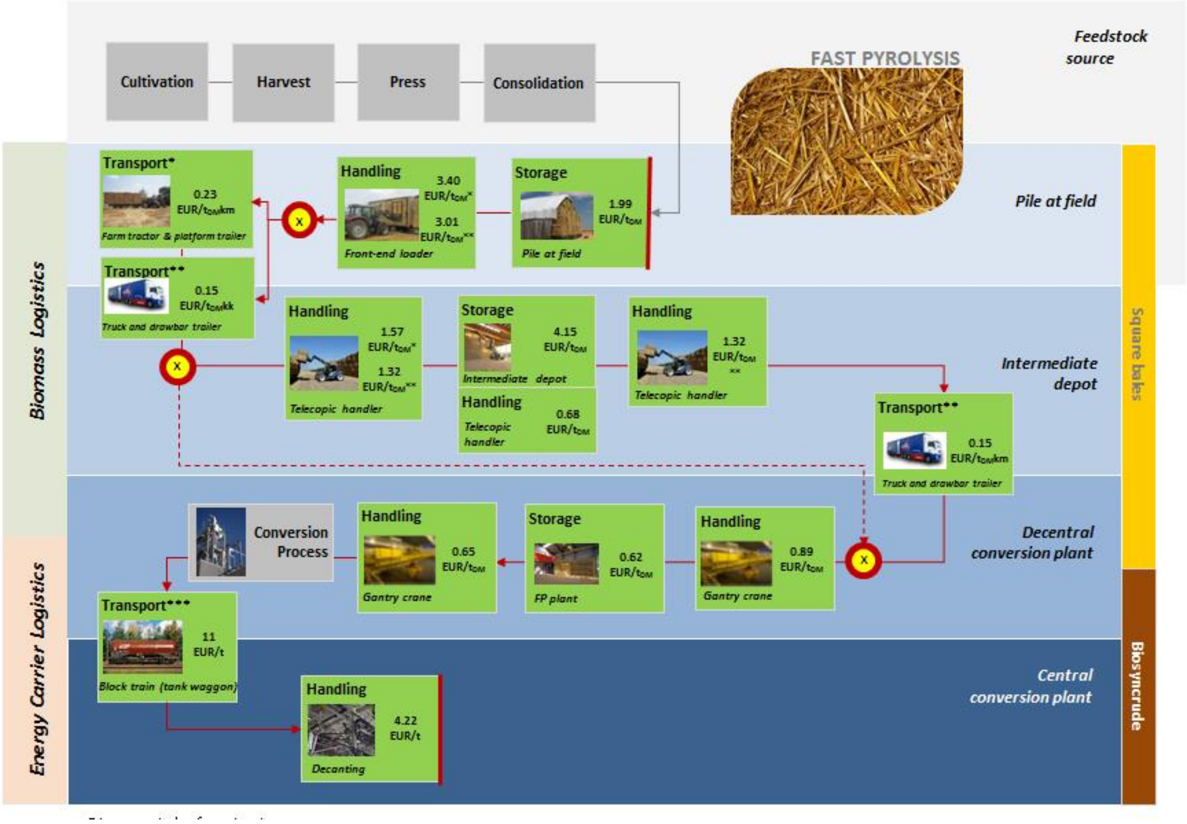
Table 6: Specification of decentral conversion processes

Decentral conversion process	*Unit*	Fast Pyrolysis	Catalytic Pyrolysis	Hydrothermal Carbonization
Energy production capacity	MW/yr	88.2	50.0	5.1
Input (biomass)	t DM/d	600	505	66
Output (energy carrier)	t/d	406	132	46
Mass conversion factor		0.68	0.25	0.69

Data in this table for the biomass quantity per day comes from the assumed sizes of approximately 175,000 tons net capacity per year. As was described before a net capacity requires higher gross quantities due to dry matter losses. The ration between output and input quantities depends on the conversion technology.

3.2.1. Energy carriers and the resulting logistics

In the same way as for biomass logistics we analysed transport opportunities and handling assets for energy carries. This finally leads to reference logistics pathways for the three conversion technologies, which are shown in detail in Figure 6 to Figure 8.



* transports by farm tractor
** transports by truck
*** transports by rail

Figure 6: Logistics reference pathways for fast pyrolysis

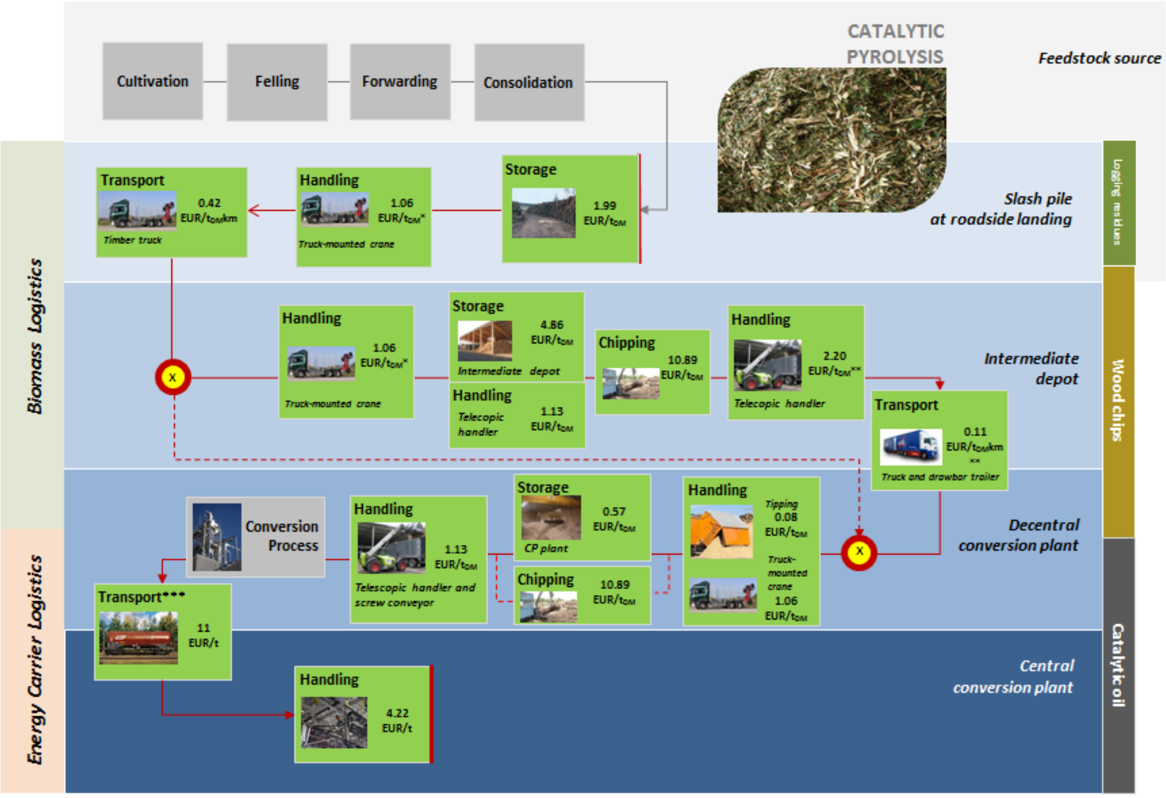
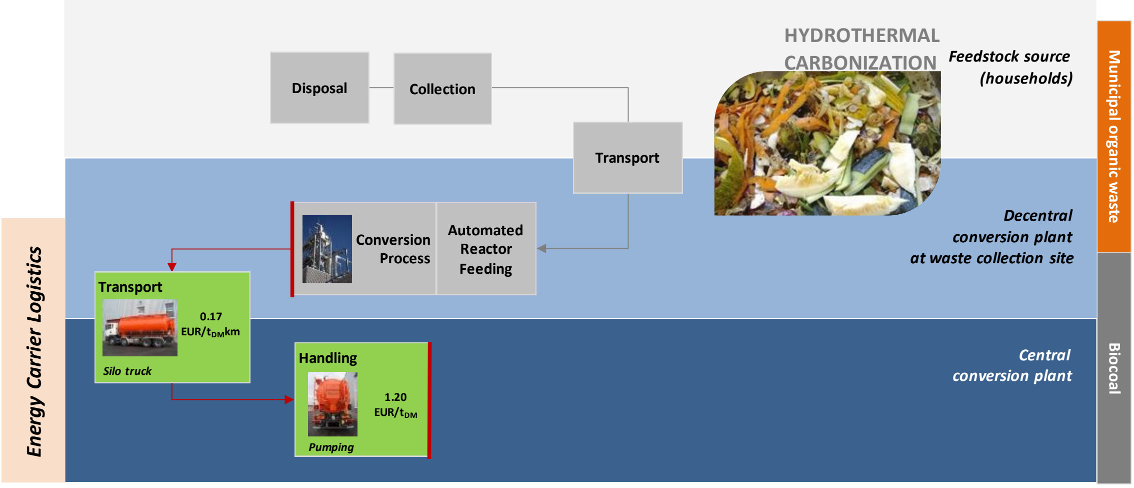


Figure 7: Logistics reference pathways for catalytic pyrolysis



* transports by farm tractor
** transports by truck
*** transports by rail

Figure 8: Logistics reference pathways for hydrothermal carbonization

Rail transports are charged at fixed costs per wagon for ranges of certain travel distances. The values shown in Figure 6 and Figure 7 assume transport distances below 200 km from the de-central to the central plant, which is line with the view of many practitioners and research papers. If distances grow the cost benefit of rail compared to road will even get more significant.

4 Risk Assessment

The risk assessment covers aspects of logistics processes (transport, handling and storage) that might be harmful to environment, to the operation itself or to society. We have analysed the most important hazards based on existing literature, regulations and expert interviews. Identified risks have then been characterized in terms of causes and effects and finally evaluated based on expert assessments, which follows a risk matrix scheme. Finally, risk mitigation actions have been determined for so-called *unacceptable risks*. This process of risk assessment has eventually lead to a safety concept that also contains related costs.
In the risk assessment it is necessary to focus on (logistics) processes and materials alike to identify risks. In total, eight different materials have been investigated, which are:

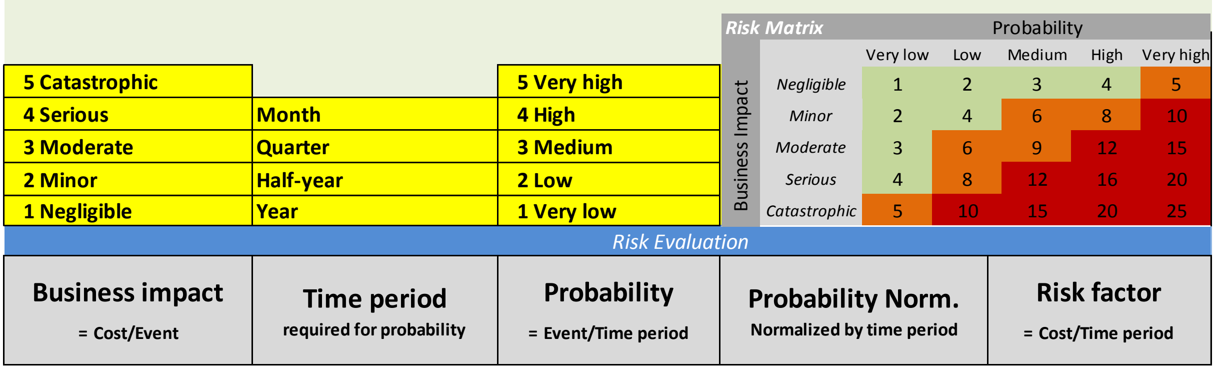
(i) reference feedstock: logging residue bundles, wood chips, straw square bales and municipal waste,
(ii) reference energy carrier: biosyncrude, biocoal, catalytic oil and
(iii) a side product: extracted phenolics.

The two latter product categories represent dangerous goods, which are subject to legislative regulations. Therefore, legal requirements for transporting dangerous goods have been included in the review.

4.1 Risk Assessment Framework

As methodological foundation an assessment framework has been devised for managing the risks. Basically, potential hazards along the BioBoost supply chain have been seized according to the following scheme: (i) risk identification, (ii) risk characterization, (iii) risk evaluation and (iv) risk mitigation. Risks have been identified from literature sources and from interviews with experts in the biomass business.

After identifying the risks, a risk evaluation followed in order to define (and finally rank) the most important risks. The structure shown in Figure 9 has served as a framework for the BioBoost project partners to define and rate risks.



5 Catastrophic		**5 Very high**
4 Serious	**Month**	**4 High**
3 Moderate	**Quarter**	**3 Medium**
2 Minor	**Half-year**	**2 Low**
1 Negligible	**Year**	**1 Very low**

Risk Matrix

Business Impact	Probability: Very low	Low	Medium	High	Very high
Negligible	1	2	3	4	5
Minor	2	4	6	8	10
Moderate	3	6	9	12	15
Serious	4	8	12	16	20
Catastrophic	5	10	15	20	25

Risk Evaluation

Business impact	**Time period**	**Probability**	**Probability Norm.**	**Risk factor**
= Cost/Event	required for probability	= Event/Time period	Normalized by time period	= Cost/Time period

Figure 9: Structure of risk evaluation

Based on literature reviews we define risk as the potential of adverse effects (towards economic achievements, society, environment, etc.). Risks can be quantified as the product of the probability and the (business) impact it might have.

$$\boldsymbol{Risk}\left(\frac{Consequence}{Time}\right) = \boldsymbol{Probability}\left(\frac{Event}{Time}\right) \times \boldsymbol{Impact}\left(\frac{Consequence}{Event}\right)$$

Probability represents the occurrence rate of a hazardous event within a specified time period. *Hazard* is an act or phenomenon that poses potential harm to persons, things, environment or society. The (*business) impact* describes consequences which a certain event might have. The adverse effects may evolve in different fields, i.e. product quality and quantity, environment, human health or technical equipment.

Following the equation above, the business impact as well as the probability of occurrence of each hazard have been evaluated according to an operationalized scale (range between 1 and 5 indicating the severity of each risk). In addition, we have added time to better describe the severity of each risk. Depending on the effect an event has with respect to time, the probability has been normalized by a certain factor. Risks that are closer are more severe and need a more thorough consideration. Multiplying the defined business impact by the normalized probability yields the so-called risk factor. Eventually, risk factors can be ranked by their numbers. The risk matrix as illustrated in Figure 9 has been split into three risk categories (see Table 7). Only the category with the highest risk has been further investigated with respect to risk mitigation actions. Risks with lower risk factors definitely exist but are lower in priority.

Table 7: Subgroups of risk categories from the risk matrix

Risk factor		from		to	
🟩	Low risk	1	≤	5	Acceptable
🟧	Mid risk	5	≤	10	Undesirable
🟥	High risk	10	≤	25	Unacceptable

We propose to evaluate risks in order to determine the so-called risk portfolio, which can be seen in Figure 10. Identified risks are arranged according their business impact (y-axis) and probability of occurrence (normalized by time period, x-axis). Moreover, the scope of each hazard, i.e. the number of influencing areas, is displayed in the form of the bubble size. As suggested by Table 7, risks with a factor greater than 10 are further investigated.

The proposed risk portfolio is set up based on the mean values of business impact and probability for all conversion technologies.

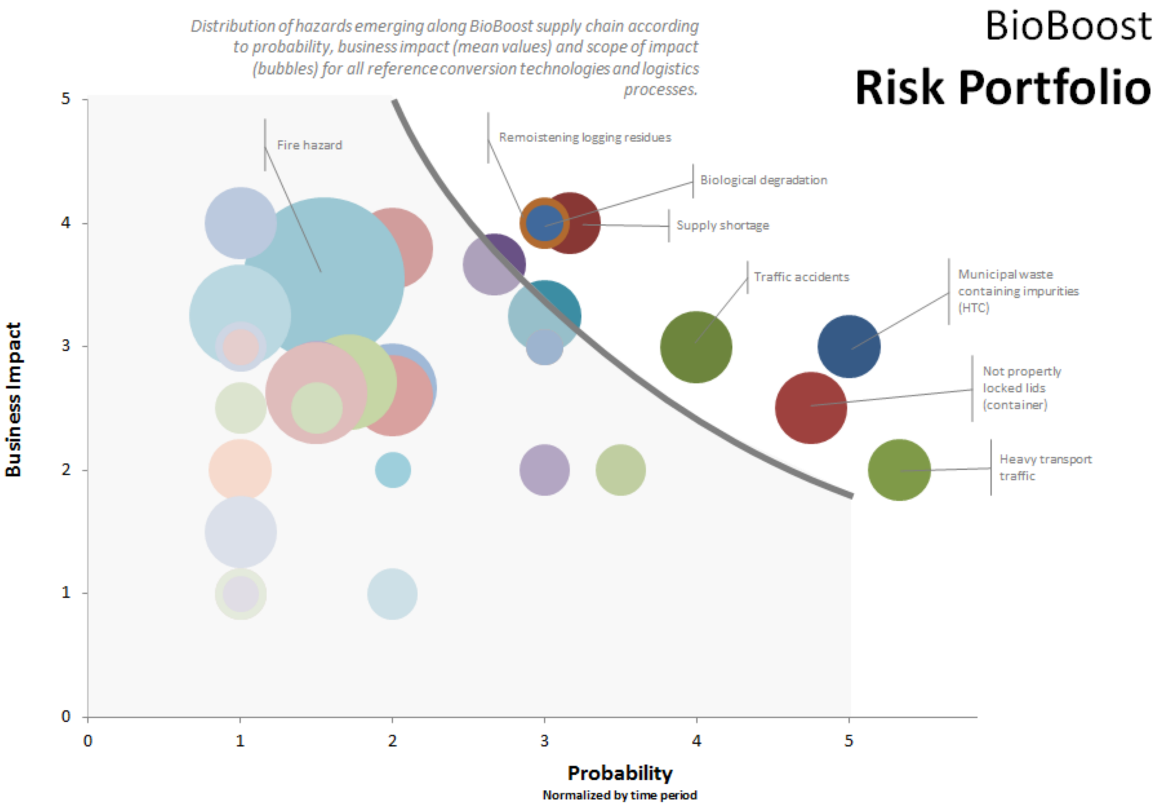


Figure 10: Risk portfolio

4.2 Risk mitigation in BioBoost and the safety concept

It is crucial to systematically identify risks but this process is useless without activities to reduce or eliminate them. So, we have collected possible actions for risk mitigation by applying a systematic literature review and expert interviews (see Table 8) and have described them in detail. This is an essential step to minimize or eliminate occurring risks.

Table 8: Actions for risk mitigation

BioBoost Risk Portfolio	Actions for Risk mitigation
Municipal waste containing impurities	Pretreatment
Supply shortage	Invest in intermediate depots
Traffic accident	- (Exogenic force)
Biological degradation	Storage location & time, Storage replenishment policy (FIFO)
High moisture content	Selection of feedstock (quality management), storage time
High share green state (needles, leaves)	Selection of feedstock (quality management)
Wrong particle size	Chipping process at SC echelon, quality management
Not properly locked lids	Staff training
Heavy transport traffic	Transportation Impact Analysis (TIA)

In the following the most important risk-mitigation actions are described.

- **Pretreatment:** To avoid any dirt in the biomass which can lead to considerable damage of equipment and consequently to loss of production, an appropriate pretreatment of the raw biomass is necessary. This can happen either upstream at the supplier or at the conversion plant using specific equipment. Activities for pre-treating material cost money. However, these costs are considered in prices or investment costs, which serve as input data to the logistic model.

- **Investment in intermediate depots:** To minimize or avoid supply shortages, the use of intermediate depots should be considered. The costs of intermediate depots have already been collected and calculated and hence are part of the simulation model.
- **Biological degradation**: Biological degradation is a direct effect of inappropriate storage. Degradation is accelerated by other factors (e.g. high humidity in raw biomass). A proper risk mitigation action is therefore prompt processing while considering required moisture contents.
- **High moisture content and high share of green state**: This risk can be minimized by appropriate quality management in goods delivery to make sure that biomass is only accepted if it meets the minimum requirements. Quality characteristics of biomass (e.g. moisture content) need to be defined in contracts with suppliers. Of course, increasing quality requirements generally leads to higher feedstock costs.
- **Wrong particle size:** The risk of a wrong particle size is also reduced by adequate quality management or eliminated with a subsequent chipping process, which is however expensive.
- **Not properly locked lids:** Not properly locked lids of tank containers and tank wagons can lead to spills and subsequently cause damage to humans and the environment (e.g. groundwater contamination). To minimize this risk sufficient employee training is necessary.
- **Heavy transport traffic:** High production throughput at conversion plants induces correspondingly high frequency of arrivals and departures of transportation vehicles. Traffic impact analysis (TIA) for inbound transport flows has shown that no traffic impact study is required for the current system assumptions. Despite this fact, traffic always increases risk since accidents might occur and road infrastructure might be damaged.

5 Simulation Model

The BioBoost simulation model has been implemented as a software component using the general purpose programming language C# and has been integrated into the open-source heuristic optimization framework HeuristicLab. The simulation model is configured using data from the configuration file and can then be used to calculate the overall costs for a given scenario for a whole year.

The simulation model facilitates evaluation and analysis of different scenarios. A scenario describes a particular assumed setting with fixed plant locations, fixed plant capacities and a fixed transport network. Together with all the data values from the data model this allows to calculate overall costs and profits for that particular scenario. The optimization of plant locations, capacities and the logistics network is external to the simulation model and is described further down below.

5.1 Overview

The simulation model performs calculations in several steps which are aligned with the major steps in the value chain shown in Figure 2. In each step the necessary input values for the next step are calculated and additionally intermediate results are produced after each step. In the following we describe the details of the BioBoost simulation model, highlighting the most relevant features.

5.2 Regional Aggregation Approach

The simulation model operates on a regional level using a map of NUTS-3 regions in Europe [NUTS2008] and therefore supports analysis of costs on a relatively fine-grained regional level. Different feedstock potentials, cost factors and average route lengths are considered within and between all regions. Moreover, regional differences in e.g. labour or investment costs or feedstock prices variations are appropriately modelled in the simulation model. Regional difference such as larger or smaller feedstock availabilities obviously have a strong impact on the simulation results. Scaling factors on a national level also allow modelling relative differences in the labour costs or fuel costs in regions.

Another, less obvious but equally important regional effect is the quality of the road infrastructure. When considering actual route lengths between regions, there is a very strong bias for plants along strongly connected routes. In the simulation model we approximate transport costs using average route lengths between regions which naturally leads to a bias for plants in well-connected regions. We have seen this effect numerous times in our simulation results where transports didn't occur to the seemingly closest neighbours but to regions that are well connected by roads or rail infrastructure. The data for the route length estimation has been gathered from Open Street Maps.

5.3 Data Model

The basis for the simulation and optimization software tool is a complete data model which provides all necessary information for the simulation of scenarios. Based on the required results and the necessary intermediate calculations the following essential data are necessary.

- The total available technical **feedstock potentials** for each considered region and each feedstock type in tons per year[3] [t/a].
- The estimated **feedstock market price** at roadside as a function of the total feedstock utilization for each considered region and each feedstock type in Euro per ton[4] [€/t].
- Estimated **average transport distances** between each pair of regions and inside each region for collection to a local plant for both road and rail transports in [km].
- Possible **transport modes** for each feedstock and product type as well as **costs and emissions for** each possible combination of transport mode and transported material as costs [€/tkm] and emissions [t/tkm].
- **Cost and emissions** for handling of material before and after transport for each possible combination of transport mode and transported material in [€/t] and [t/t].
- Average yearly **storage costs** for each feedstock type (including energy carrier intermediates) in [€/t] as well as the number of days of safety stock for each conversion technology.
- For the conversion technologies a large volume of background information or facts are necessary. First, a **design size as well as the minimum and the maximum allowed size for plants** have to be specified for each conversion technology in [t/a].
- Moreover, the annual amortized **capital investment costs** in [€/a] and the **operation costs** in [€/t] for a plant of the specified design size are required.
- For each conversion technology two **scaling factors** which relate the increase in operating and capital investment costs to plant size. It is assumed that larger plants can be operated with a lower cost relative to the throughout up to a maximum capacity (economies of scale [Sull2003]).

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[3] Feedstock amounts given in tons are considered tons of dry mass.

[4] A detailed description of the feedstock market price curve is given below.

- For each conversion technology the **consumed inputs** (products and energy) as well as the **produced outputs** for a plant of the specified design size have to be specified per ton of feedstock in [t/t] or [MWh/t]. In the simulation we assume that conversion is performed using only a single feedstock type or a fixed mix of feedstock.
- **Costs for each consumed input as well as produced output** in [€/t] or [€/MWh]" Products which are actually waste products or emissions have an associated negative price i.e. they are "sold" but actually produce a debt. This list, therefore, includes **average emissions** such as CO_2 or particulate matter for the conversion of a certain amount of feedstock [t/t].
- **Locations and free capacities of refineries** in Europe: as processing units for catalytic pyrolysis oil have to be collocated for the economic utilization of hydrogen. We assume that bio-oil from catalytic pyrolysis can be most efficiently processed in plants co-located to larger refineries.
- Finally, **national scaling factors** for the following cost categories (investments, labour, fuel, maintenance, and other) are part of the data model and allow regional scaling of costs.

The values for all these variables have been collected and prepared mainly by TNO in cooperation with all other partners in the BioBoost consortium. The data model determines the structure of the data file which contains all data for the simulation and uses a YAML-format. A small fragment of this data file containing the specification for the fast pyrolysis process is shown below.

```
conversions:
  - label: FastPyrolysis
    feedstock: Straw
    safety-stock: 365 # days
    dry-matter-loss: 0.025 #percentage
    storage: # [EUR/t/a]
      investment: 1.15
      labor: 2.75
      other: 2.85
    products: # [t/t] names and mass ratios
      Biosyncrude: 0.675676
      CO2: 0.324324
      WaterVapor: 0.108108
      CoolingWater: -0.344595
      ElectricityIn: -0.087838
    cost: 0 # [EUR/t] variable cost without feedstock cost or supplies
    design-capacity: 219123.38028 # [t/a]
    construction: 11003716.52 # [EUR/a]
    min-construction: 1743968 # [EUR/a] (1/10)^0.8 of design size const. cost
    maintenance: 7278442.59 # [EUR/a]
    min-maintenance: 727 844.259 # [EUR/a]
    construction-scaling-exponent: 0.8 # factor
    maintenance-scaling-exponent: 1 # factor
    utilization-factor: 0.9

    available-capacities: { FR614: 2000000 } # [t/a] no construction cost
    available-maintenance-factor: 1 # = same maintenance as non-collocated
    max-capacities: { Default: 0, FR614: 200000000000 } # [t/a]
```

5.4 Calculation Model

The calculation steps of the simulation model are aligned with the value chain from feedstock acquisition to utilization of the final product. The necessary inputs for the simulation model are the feedstock utilizations in each region and for each feedstock type as well as the transportation vectors for each feedstock type and region. In the following sections, the feedstock utilizations are modelled as the function $u(p, r)$ and the transport targets are modelled as the function $t(p, r)$, where *p* represents the product and *r* stands for the region.

Intuitively, the goal of the optimization should be optimized plant locations and capacities as well as a logistic network for the delivery of feedstock and intermediate energy carry to and between plants. When the optimization problem is formulated in this way, the locations and capacities of plants as well as the sourcing regions for feedstock for each plant are considered as variables, and the acquired feedstock amounts, as well as plant capacities would have to be limited using constraints. Within BioBoost, we decided early on to formulate the optimization problem in an alternative way which eliminates the necessity for constraints for feedstock amounts and automatically determines optimal plant capacities. In this formulation only the feedstock utilizations for each region and feedstock type as well as the transport target region for each feedstock source region are considered as variables and we assume that a plant of the correct size is necessary in each region where feedstock is transported to. Therefore, in this formulation the plant locations and capacities are implicitly determined which greatly reduces the number of possible scenarios and prematurely excludes futile scenarios.

Given the utilization vectors and the transport target vectors and all the values from the data model the calculations are performed in the following steps:

1) **Feedstock Acquisition:** The acquired feedstock amounts and costs are determined based on the feedstock potentials and utilizations.
2) **Feedstock Transport:** Using the choice of transport mode, with the help of the distance matrix, the costs are determined based on the feedstock amounts and the transportation target. In this step the simulation model automatically chooses the most efficient transport mode given the choice of target region and product. This can be determined locally. Based on the transportation vectors and the acquired feedstock amounts it is easy to calculate the feedstock amounts at the transportation targets.
3) **De-central Processing:** Optimal olant capacities are automatically derived based on the feedstock amounts at the target. Notably, the BioBoost simulation model is not parameterized with plant capacities but instead the plant capacities are determined indirectly through feedstock utilizations and transport vectors, as it is assumed that all feedstock that is delivered in a region has to be processed in a plant. Therefore, the simulation model always assumes a plant with ideal capacities based on the available feedstock. To adapt plant capacities it is necessary to either change utilization or transportation targets. Calculation of operation costs and investment costs for the plant is based on its capacity. The simulation model assumes that processing in a plant requires a set of input products and yields a set of output products. An intermediate result of this step are storage costs which are determined based on the feedstock amounts that are processed at each plant.
4) **Energy Carrier Transport:** Output products from plants can be further transported to other regions for further processing. The simulation model considers only energy intermediates for further processing, while side products and emissions are dealt with locally. The transport vectors for energy intermediates are parameters for the simulation models similar to the transport vectors for biomass. Analogous to step (2) the simulation model determines the optimal transport mode and transport costs for energy intermediates.

5) **Central Processing:** Energy intermediates are further processed at plants to produce either transport fuel (refinery), synthetic gas (gasifier), or directly converted to heat and electric energy in combined heat and power plants.
6) **Disposal:** The calculation model includes a final step in which the costs for the disposal of wastes and emissions, or the revenues from the sales of the main products or side products are determined. This step is necessary for an overall profitability analysis.

5.5 Estimation of Realistic Feedstock Market Prices

The simulation model includes an approximation model for feedstock price that depends on market saturation. If the BioBoost conversion technologies are implemented on a larger scale in Europe, we have to assume that prices for the considered feedstock increase as the demand rises. By including a price approximation model in the simulation model it is possible to accurately estimate increasingly higher feedstock costs for a potential ramp-up scenario where we expect that a larger fraction of the available feedstock amounts are converted. The feedstock price is determined on a regional level, taking into account the regional potential, the regional utilization and the already-established price development. Figure 11 shows the price curves for three feedstock types used in the reference scenarios.

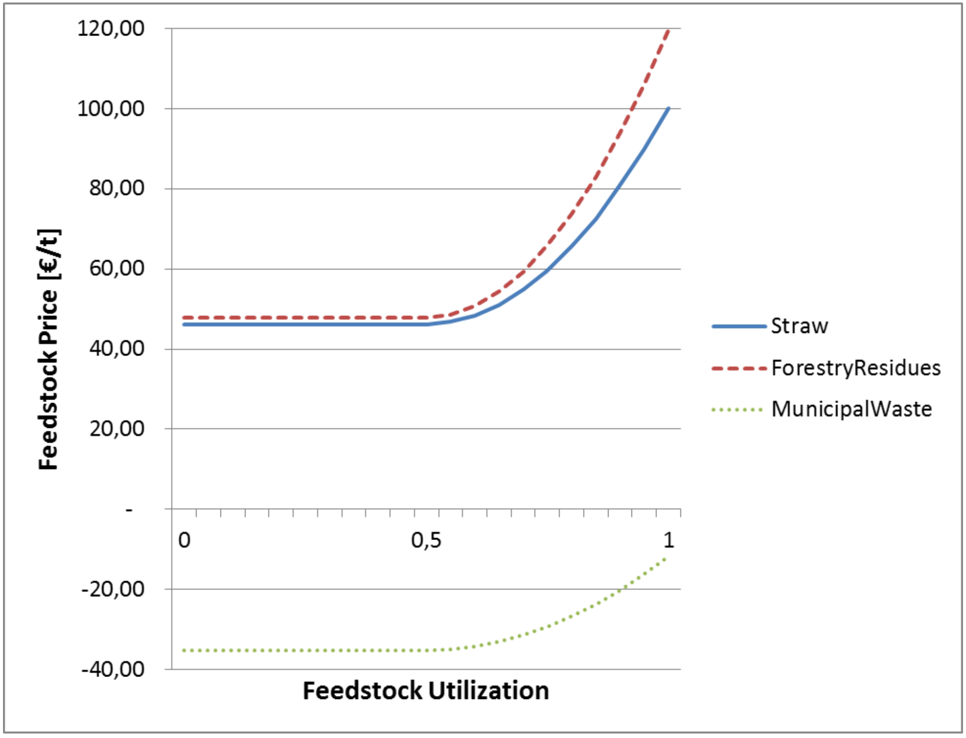

Figure 11 Default price/supply curves

Each price curve is determined by two parameters, the base price and the maximum price. The base-price is the price for utilizations between 0% and 50%. The maximum price represents the assumed price at 100% utilization. Accordingly, a fixed price is used for utilizations up to 50%; from which on a quadratic function is applied that starts with a gradient of zero and goes through a defined point at 100% utilization. More details on the price curve model and the determination of base price and maximum price for each feedstock type are given in BioBoost Deliverable 1.1 – "Feedstock costs".

5.6 Routing

The calculation of actual routes on arbitrary points on the map is not feasible for European-wide scenario, especially, when millions of scenarios need to be considered. Therefore, we had to settle for a reasonable estimate within the simulated scenarios. Given the previous aggregation step to consider regions as a whole, it is only natural to also consider routes between regions instead of individual coordinates.

Conventional routing algorithms, however, take several seconds to derive good (not even optimal) routes on a road network as large as Europe's. For this reason considerable effort has been devoted to a reasonable compromise between speed of evaluation and quality of the results. In particular, we do not calculate routes on-the-fly but have prepared a large distance matrix with route estimates between and inside regions.

In a first step 30 random points are generated for each region. These points are then used to find the closest road intersection as shown in Figure 12. Using these intersection points averages are calculated for both the route length within a region, i.e. for de-central feedstock collection as well as for the route lengths between regions.

For this purpose more than 10 million routes had to be calculated which would have taken weeks with conventional algorithms. Therefore, we have employed so called contraction hierarchies [Geis2008] which are able to rapidly calculate exact routes by using extensive hierarchical routing with prepared "shortcuts".

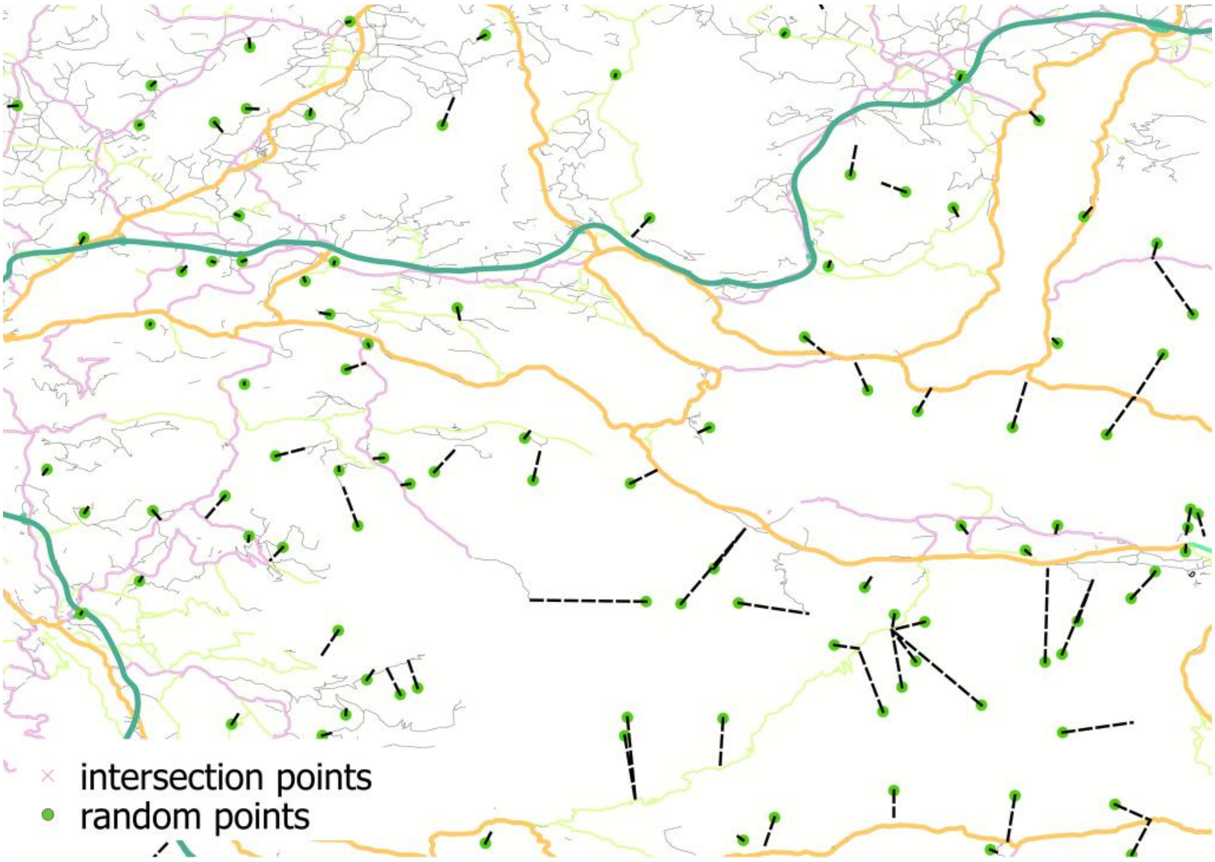

Figure 12 Mapping of Random Points to Roads

5.6.1. Automatic Regional Subdivision

For larger regions with a large feedstock potential, aggregation of all feedstock to a single de-central plant might create scenarios that are sub-optimal. The reason is that the amount of feedstock would suffice to drive several de-central plants which could be located at more favourable locations in terms of transport distance inside a single region. Of course, this has to be counterbalanced with the economy of scale for larger plants.

For this reason, we have created a geographical model that further subdivides regions into a certain number of sub-regions in a first step. In a second step, we calculated a new distance matrix containing routing factors for the resulting region set.

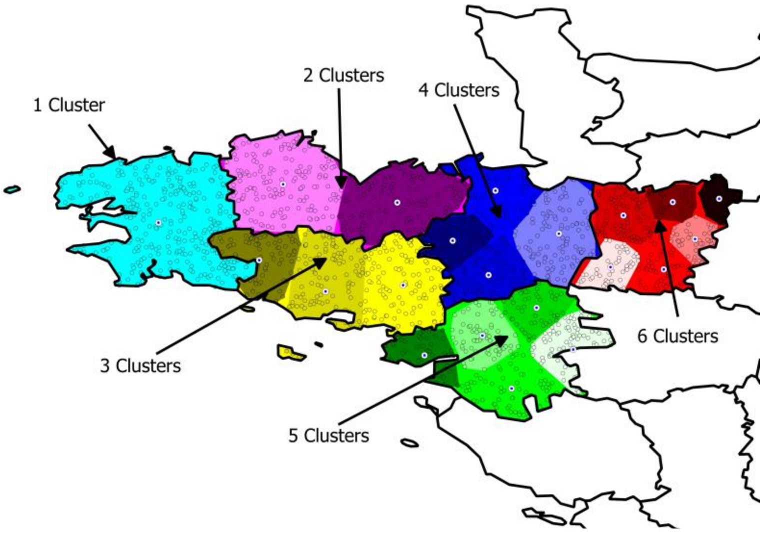

Figure 13 Examples of region with increasing number of sub-regions

Figure 13 shows some examples for regions with sub-regions. Depending on the number of regions, the shapes and, hence, the distances can vary. The regions have been divided in a way to limit the area of any region to 7500 km^2. This sub-division does not consider the underlying road network. Therefore, it is possible that other sub-divisions might provide even better reduction of transport costs.

5.7 Plant Location and Capacity Constraints

The optimization model supports the definition of constraints and minimum as well as maximum plant capacities on a regional level which implicitly allows constraining plant locations[5]. This is important because it has to be assumed that the feasible regions for plants are only a small subset of all considered regions. For example, processing of bio oil from catalytic pyrolysis to transportation fuel is only feasible in a refinery where free capacities of hydrogen are easily available.

This information is used for the exclusion of certain possibilities of transport targets and for limiting plant size to available capacities as constrained by free capacities in the case of co-location. For each conversion technology the maximum allowed capacity for each region can be specified the data model.

This feature has been used to limit the locations and capacities for central processing plants for catalytic pyrolysis oil. In the data model we specified that bio oil can only be processed to transport fuel in selected existing refineries in Europe. We assumed that refineries with a conversion capacity of at least 10 Mt/a of crude oil have the necessary facilities for co-location of CP oil processing units. We assumed that there are enough capacities to co-

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[5] By setting the maximum allowed capacity for a plant type and a region to zero the optimization model automatically detects that a plant of that type is not allowed in this region.

process maximally two percent of CP oil. Locations of those refineries have been mapped to the list of NUTS3 regions and the maximum capacities for CP oil refinery plants in these regions have been constrained to two percent of the existing refinery capacity in the data model. Therefore, the simulation model correctly approximates costs for transportation of CP oil to refineries and co-processing and also respects the limited refinery capacity in Europe which indirectly limits production and utilization of CP oil.

In addition we found that by leveraging the economies of scale a short-sighted "ideal" scenario would be very large plants that are, however, not feasible in terms of transport volume or social and environmental aspects of such large facilities. Therefore, the capacities of all conversion technologies have been limited to approximately 700 truckloads per day. As this and other restrictions are implemented as soft constraints to guide the optimization facilities in the final it is possible that the final solution have, for example, slightly larger plants even though a small penalty is accrued.

6 Algorithms

6.1 Metaheuristics

In the software tool for simulation and optimization developed in WP4 we provide different types of evolutionary algorithms. Evolutionary algorithms are a kind of meta-heuristic algorithm which can be applied to a large variety of different optimization problems. Meta-heuristic algorithms [Glover2003] can be used for optimization problems when it is not necessary to solve the problem exactly and it is sufficient to find a good solution. This is often the case in real-world optimization problems, for instance because input data is already inaccurate or unavailable or because finding and exact solution is computationally infeasible. We have concentrated on two evolutionary algorithm variants: single-objective evolution strategies (ES) [Rech1973], and multi-objective genetic algorithms (i.e., the non-dominated sorting algorithm NSGA-II [Deb2002]), and have adapted these algorithms to the requirements of the BioBoost simulation model. A detailed description and comparison of genetic algorithms (GA) and evolution strategies (ES) is given in [Bäck1996, Dejong2002].

Evolutionary algorithms start from a set of initial configurations ($t(p,r)$ and $u(p,r)$) for the problem which are usually initialized randomly and then iteratively generate new configurations by combining elements from a set of active configurations. The process is designed in a way to improve the quality of solutions over time. It is accomplished in evolutionary algorithms by exerting selection pressure on the configurations. Either, better configurations are selected from the active set with a higher probability (e.g. in Genetic Algorithms), or a surplus of new configurations is generated and only the best of them are kept (e.g. in Evolution Strategies). In the following sections the two algorithms are described in detail.

6.1.1. Evolution Strategies

In evolution strategies, solution candidates are encoded as a fixed-length real-valued vector. An ES is also population-based and starts with a randomly initialized population. In evolution strategies, new solution candidates are generated as stochastic variations of random parent solution candidates (mutation). The fitness of all generated individuals is evaluated and only the best ones are selected for the next generation. This is continued until a termination criterion is met. Important characteristics are population size μ, the number of offspring produced in each generation λ and whether the new population is selected from parents and offspring (called "$\mu + \lambda$"), or only from the offspring (called "$\mu\,,\ \lambda$"). In addition to mutation, recombination can be used to create new individuals out of two or more parents. Several improved version of ES have been formulated including self-adaptive variants. A simple ES algorithm is shown in Figure 14.

```
Parameters: fitness function F, $\mu$, $\lambda$, maxGenerations
Results: BestSolution

 $g \leftarrow 0$
 $\text{Population}_g \leftarrow$ create $\mu$ individuals randomly
 $\text{BestSolution} \leftarrow \text{argmax}_{s \in \text{Population}_g} \text{F}(s)$
 WHILE $g < \text{maxGenerations}$ DO
    $\text{OffspringPopulation}_g \leftarrow \text{Population}_g$    // $(\mu + \lambda)$ ES
    WHILE $|\text{OffspringPopulation}_g| < (\mu + \lambda)$ DO
      $p \leftarrow$ select random parent
      $c \leftarrow$ create stochastic variation of p
      $\text{OffspringPopulation}_g \leftarrow \text{OffspringPopulation}_g \cup \{c\}$
      IF $\text{F}(c) > \text{F}(\text{BestSolution})$ THEN
         BestSolution $\leftarrow$ c
      END IF
    END WHILE
    $\text{Population}_{g+1} \leftarrow$ take μ elements from $\text{OffspringPopulation}_g$ with best fitness
    $g \leftarrow g + 1$
 END WHILE
```

Figure 14: Evolution Strategy

6.1.2. Genetic Algorithms

In genetic algorithms, solution candidates are represented as fixed-length chromosomes (either a binary or an integer vector). The algorithm manages a population of solution candidates which is initialized randomly. The primary operator in GAs is genetic crossover, which creates new solution candidates by combining parts of two parents. Additionally, mutations can be applied to increase the diversity of the population. Parents are selected based on their relative fitness. The algorithm terminates when a predefined number of generations has been evaluated. Important parameters are population size, selection strategy, crossover strategy, and mutation rate. Figure 15 shows the pseudo-code of a simple GA.

```
Parameters: fitness function F, popSize, mutationRate, maxGenerations
Results: BestSolution

$g \leftarrow 0$
$\text{Population}_g \leftarrow$ create popSize individuals randomly
$\text{BestSolution} \leftarrow \text{argmax}_{s \in \text{Population}_g} \text{F}(s)$
WHILE $g < \text{maxGenerations}$ DO
    $\text{Population}_{g+1} \leftarrow \{\}$
    WHILE $|\text{Population}_{g+1}| < \text{popSize}$ DO
        $p_1, p_2 \leftarrow$ select parent individuals ($\in \text{Population}_g$) by fitness
        $c \leftarrow$ recombine $p_1, p_2$ (crossover)
        IF random() < mutationRate THEN
            mutate $c$
        END IF
        $\text{Population}_{g+1} \leftarrow \text{Population}_{g+1} \cup \{c\}$
        IF $\text{F}(c) > \text{F}(\text{BestSolution})$ THEN
            $\text{BestSolution} \leftarrow c$
        END IF
    END WHILE
    $g \leftarrow g + 1$
END WHILE
```

Figure 15: Genetic Algorithm

6.1.3. NSGA-II

The two algorithms described above are examples for single-objective optimization algorithms. In BioBoost it is also necessary to optimize two objectives simultaneously such as the total amount of final product produced and the overall costs that are incurred for the production. For these kinds of multi-objective optimization problems the non-dominated sorting genetic algorithm (NSGA-II) can be used. This algorithm works similarly to a genetic algorithm with the difference that selection of solution candidates is performed relative to all objective values. NSGA-II produces a set of Pareto-optimal solutions as the final result. The algorithm also starts with a random population and then repeatedly selects solution candidates for recombination and mutation. In the selection step solution candidates which are on or near the Pareto-front are selected with a higher probability. After a certain number of new solution candidates have been produced truncation selection is performed to keep only the best solution candidates from the current generation and from the pool to produce the population for the next generation.

A benefit of multi-objective optimization algorithms is that the final Pareto-optimal solutions can be analysed and the preferable solutions can be chosen a-posteriori.

6.2 Solution Representation

Evolutionary algorithms require that a scenario is represented as a structured datatype (encoding). As described above the standard definitions for GA and ES assume fixed length integer vectors or fixed-length real vectors. For BioBoost scenarios this has to be adapted because a BioBoost scenario cannot be naturally represented as an integer vector or a real vector. A BioBoost scenario is therefore represented as a solution candidate composed of two parts, the first part encodes the transport target function $t(p, r)$, the second part encodes the utilization function $u(p, r)$. The transport target is represented as an associative array containing target vectors of length $|\text{R}|$ for each product, where R is a vector of regions, in our case regions of Europe equal to or derived from NUTS3 regions.

The feedstock utilization function is also encoded as an associative array and contains a utilization vector of length |R| for each feedstock where each element is in the range [0..1]. An exemplary solution candidate for a scenario in which only straw is considered as biomass feedstock and biosyncrude is the only type of intermediate is shown in Figure 16.

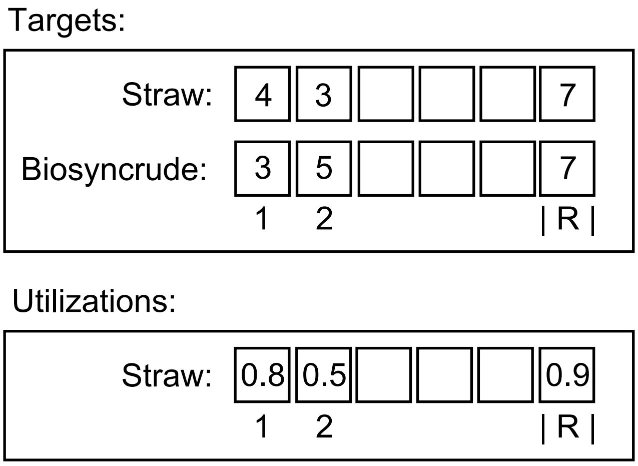

Figure 16 Example for a scenario encoded as a solution candidate for evolutionary algorithms

Evolutionary crossover operators take two solution candidates as input and produce a new solution candidate by combining the information from both inputs. In this operation each part of the solution is handled independently. This means that all elements of associative array for transport targets and all elements of the associative array for utilization are crossed over independently. One of the frequently used crossover operators is the single-point crossover, which takes two vectors u and v, selects a random cutting point $c \in [1 \; .. \; |\mathrm{R}| - 1]$, and then generates a new vector w by concatenating the first part of u and the second part of v, $w = u_{1..c}\; v_{c+1..|\mathrm{R}|}$. Figure 17 shows an example of a single-point crossover operation.

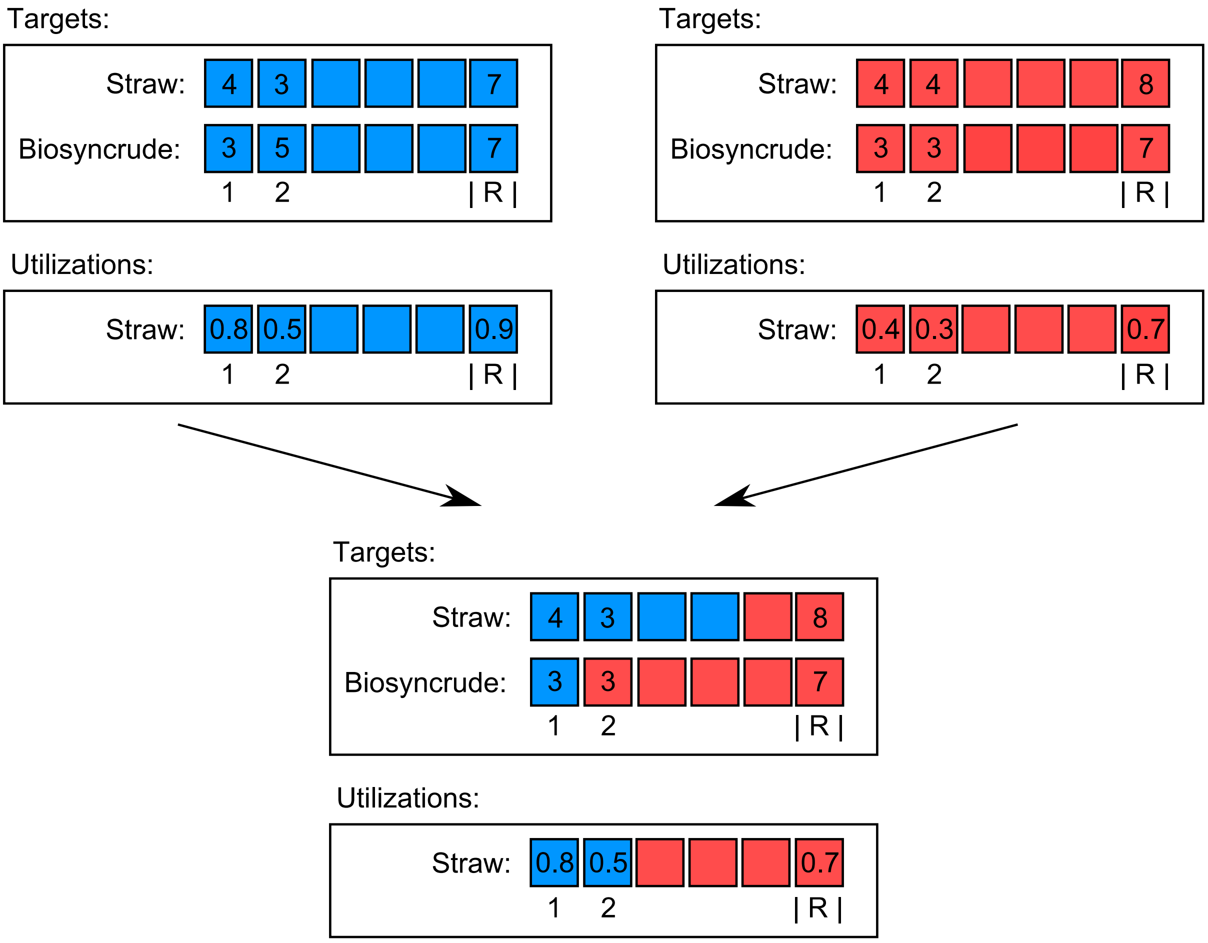

Figure 17: Example for Single-Point Crossover

In the optimization environment different types of crossover operators are supported and multiple crossover operators can be active during a single optimization run.

Mutation operators make a small change to a solution candidate, for instance changing one target region or adding a small random number to the feedstock utilization of a region. Again multiple different mutation schemes are possible. Mutation is usually necessary to increase the genetic diversity of a population and improve the convergence behaviour of genetic algorithms.

6.3 BioBoost-specific Adaptations to the Optimization Algorithms

The simultaneous optimization of transport network and feedstock utilizations (or alternatively plant locations and capacities) that is necessary in the BioBoost project is challenging because the optimization of the transport network is interrelated to the optimization of the feedstock utilization vectors and vice-versa. Standard variants of meta-heuristic optimization problems cannot be used in a straight-forward manner and have to be adapted accordingly. In the following sections we describe some of the necessary adaptations.

6.3.1. Problem-specific Evolutionary Operators

Experiments with standard crossover and mutation operators such as single-point crossover or single-point mutation showed that these operators are not effective for the optimization of BioBoost scenario. The reason for this is that the chosen representation has the property that there are strong dependencies between separate elements of solution candidates. This has the effect that changing only one element of the transport target vector without considering the values of the other elements most likely has a detrimental effect on the encoded scenario. Frequently, multiple such detrimental changes in a row are necessary to identify a possible improvement. Similarly, simply combining parts of two encoded scenarios through single-point crossover has a very small probability of generating an improved scenario because e.g. the neighbourhood relation between regions is completely ignored. We have therefore developed new evolutionary operators specifically tuned for optimizing BioBoost scenarios. The following operators have been implemented:

- Plant-based crossover: This operator combines two scenarios on the level of plants. If both parent solution candidates have a plant in the same region the plant will also exist in the new solution candidate. If the plant has the same supplier regions the plant in the new solution candidate will also have the same suppliers. Otherwise plants are copied with their supplier information randomly from the parents. Conflicts are resolved randomly.
- Manipulation operators:
    - Plant Splitter: Splits an existing plant into two plants of the same type, one plant is kept in the original location the second plant is assigned to one of the neighbouring regions. The set of supplier regions for the original plant is split into two sets randomly, the first set contains the suppliers to the first plant the second set contains the suppliers for the second plant. This operator only changes transport targets
    - Plant Merger: Merges two existing plants of the same type into one larger plant. Two plants are selected and the supplier regions for both plants are merged to one set of suppliers to one of the two plants. This operator only changes transport targets.
    - Plant Mover: Takes a plant and moves it to one of the neighbouring regions. This operator only changes transport targets.
    - Supplier Equalizer: Determines the set of all supplier regions for one plant (de-central or central) and equalizes the utilizations of those suppliers. This operator only changes the utilizations of supplier regions to one plant. The overall capacity is not changed only the distribution of acquired feedstock from regions is changed. This operator only changes utilizations.
    - Supplier Randomizer: Determines the set of all supplier regions for a plant and slightly changes all utilizations randomly (this is the symmetric operation to the supplier equalizer). This operator only changes utilizations.
    - Supplier Utilization Exchange: Selects two supplier regions for the plant randomly and exchanges the utilization values. This operator only changes utilizations.
    - Supplier Toggler: Selects a random supplier and either sets the utilization to zero if it is non-zero or sets the utilization to 50% if it is zero. This operator only changes utilizations.
    - Plant Killer: Selects a plant and removes it from the scenario. This operation also changes all supplier regions for the plant and set the utilizations for those supplier regions to zero. The plant killer is an essential operator when the goal is to identify the most cost-effective plant location. However, it is detrimental when the goal is to maximize produced amounts with minimal costs.

6.3.2. Two-phase Optimization of Transport Network and Feedstock Utilizations

Especially, in optimization situations where a profitable outcome is difficult and the optimal solution yields only a small profit in comparison to the turnover, the optimization has a tendency to converge to a situation where no feedstock is acquired and transported as this is a scenario that can be easily found and does not incur any costs. These cases can usually be considered premature convergence and should be avoided. A way to solve this problem is to perform optimization in two phases. In the first phase only the transport-network is optimized assuming fixed utilization vectors where 100% of the available feedstock is acquired. In the second phase, which is started when a reasonable transport network has been identified the utilization vectors are optimized together with the transport network.

6.3.3. Dynamic Solution Space Reduction

While the simulation itself has been refined to minimize per-iteration calculation time, also the optimization scheme has been improved by dynamically reducing the size of the solution space. In other words, the number of different possibilities for varying each scenario is reduced to only meaningful similar scenarios. This is accomplished by analysing the values from the data model and determining which solution candidates are feasible in a pre-processing step. This has the effect that the number of regions considered for feedstock acquisition and as transport sources can be reduced which reduces runtime of the optimization algorithm. Experiments showed that this solution space reduction accelerates convergence speed of the optimization algorithm by about 10-20% without sacrificing any feasible possibilities [Pitzer2015].

7 Software Implementation

The developed simulation and optimization environment is deployed as a simple ZIP-archive and has been provided for download on the BioBoost “intranet”-platform for all BioBoost project partners. This software module has been implemented as plugin for HeuristicLab[6], an open-source software environment for optimization [Wagner2014]. HeuristicLab provides a rich GUI and a framework for meta-heuristic optimization algorithms including implementations of most of the well-known meta-heuristics (such as Evolution Strategies, Genetic Algorithms, or NSGA-II). Therefore, HeuristicLab provided an optimal platform for the development of the BioBoost simulation and optimization environment because several components could be reused reducing the effort for the implementation.

After the end of the project the newly developed module will be integrated into HeuristicLab as a separate plugin and will be released together with official HeuristicLab releases as open-source software. HeuristicLab requires the .NET Framework and runs on Windows systems. The GUI for the simulation and optimization environment supports problem data import, adaption of data values, algorithm settings and, finally, the visualization of the simulation results. Figure 18 shows a screenshot of the software, where a solution displayed on a map.

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[6] HeuristicLab Website: http://dev.heuristiclab.com

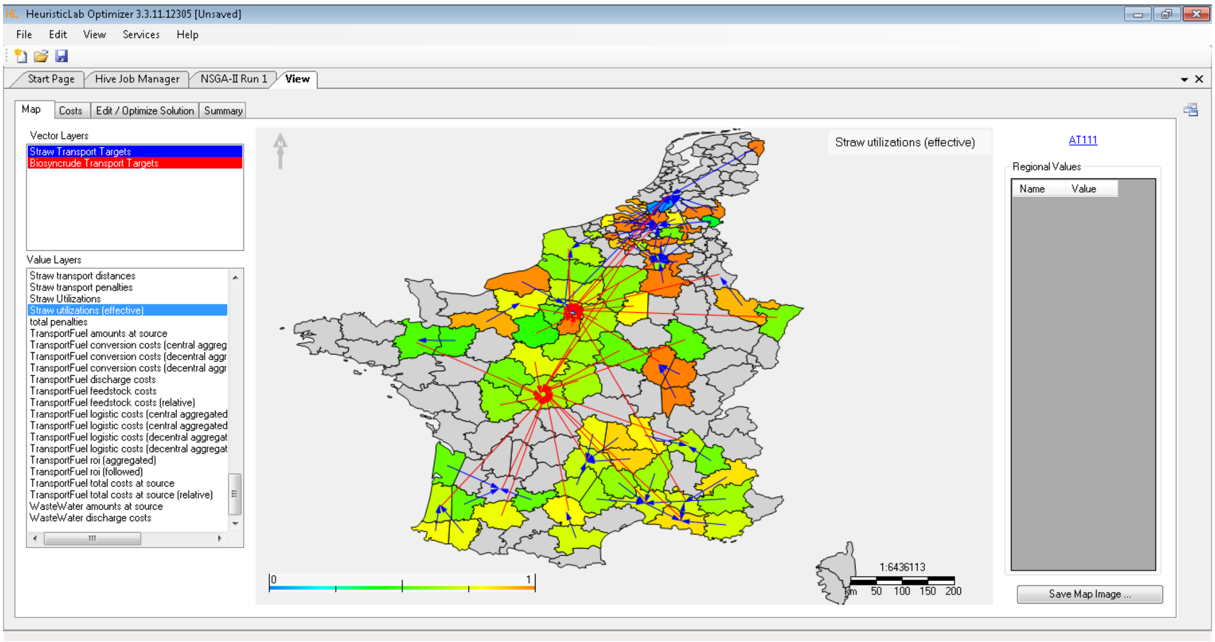

Figure 18 Screenshot of HeuristicLab Running the BioBoost Simulator

8 Results

In this section examples for results generated using the simulation and optimization software tool are shown. The following figures show the results for one of the three reference pathways on an EU-wide level where the optimization goal is to maximize the produced fuel or energy while at the same time minimizing the total costs for the production. These are contradicting goals because operating only one very cost-effective plant would only allow producing only small amounts of fuel and it is necessary to operate less cost effective plants to produce significant amounts of bio-fuels.
The maps indicate biomass transports with blue arrows and intermediate energy carrier transports with red arrows. The colour of the NUTS3 regions indicates how much of the available potential is utilized.

Several tools have been developed for the analysis of results. Figure 19 shows a visualization of the relative production cost for different plants on the left, and the corresponding transport vectors on the right. In Figure 20 a cost breakdown of the different contributing factors is shown. It contains the optimization results from two different approaches. On the top, the “ESa” result is a top scoring scenario where both the expected return-on-investment as well as the produced fuel amount have been considered with equal priority. It lists the average as well as the most expensive, the cheapest, the largest and the smallest plant. In the bottom half the same figures are shown for a slightly different optimization goal, where only the expected return-on-investment was considered. In this case, a slightly cheaper plant configuration has been found.

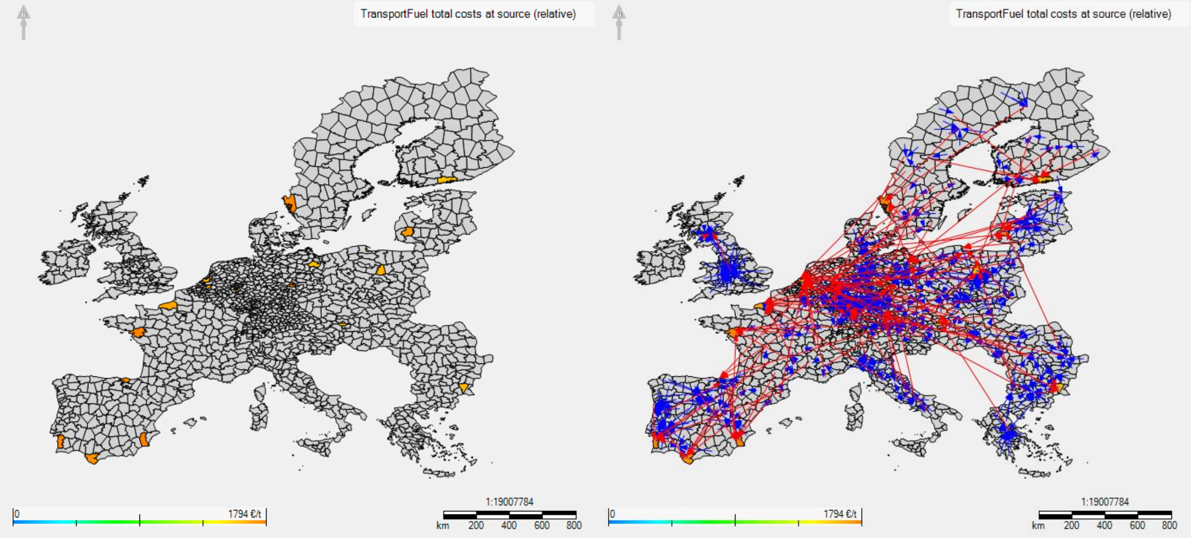

Figure 19 Plant Locations and Transport Vectors

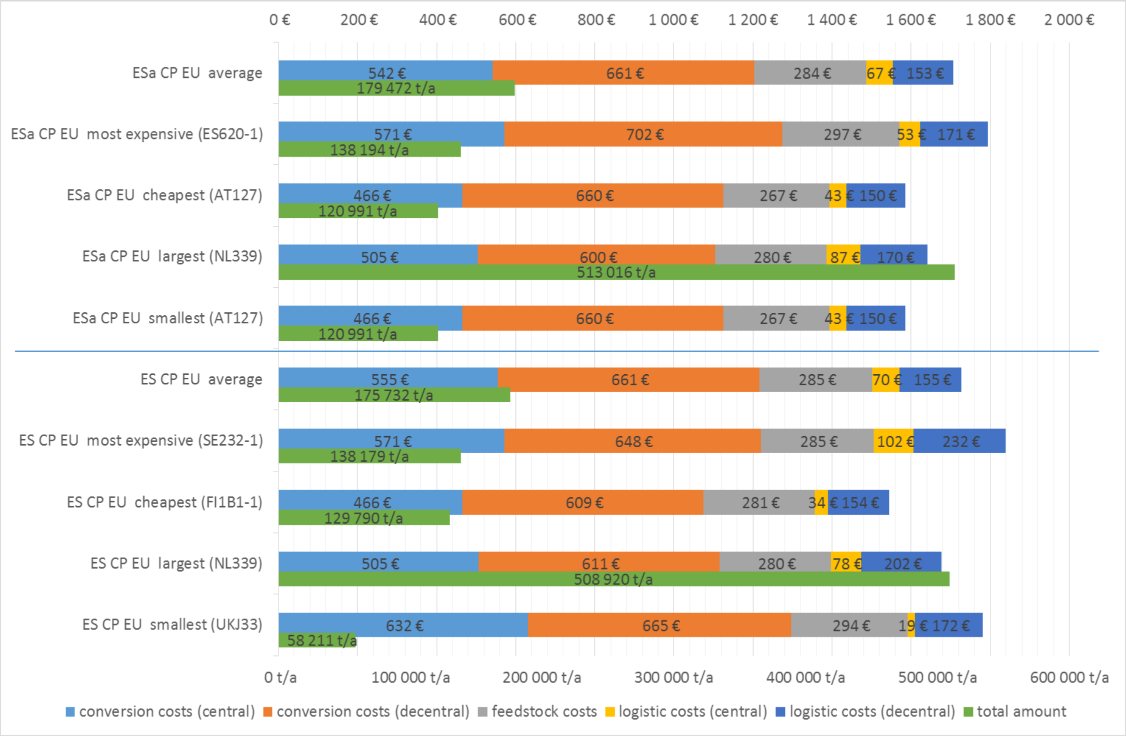

Figure 20 Cost Breakdown

It should be noted, that the results for catalytic pyrolysis might seem very unnatural as decentral plants often do not deliver to the next central plant. This is due to the limited number of locations and their limited capacities. Theses refineries need hydrogen for the treatment of the crude bio oils which is only economically viable at existing refineries. Therefore, most locations are maxed out especially since the transport of bio oil via train is comparatively cheap.

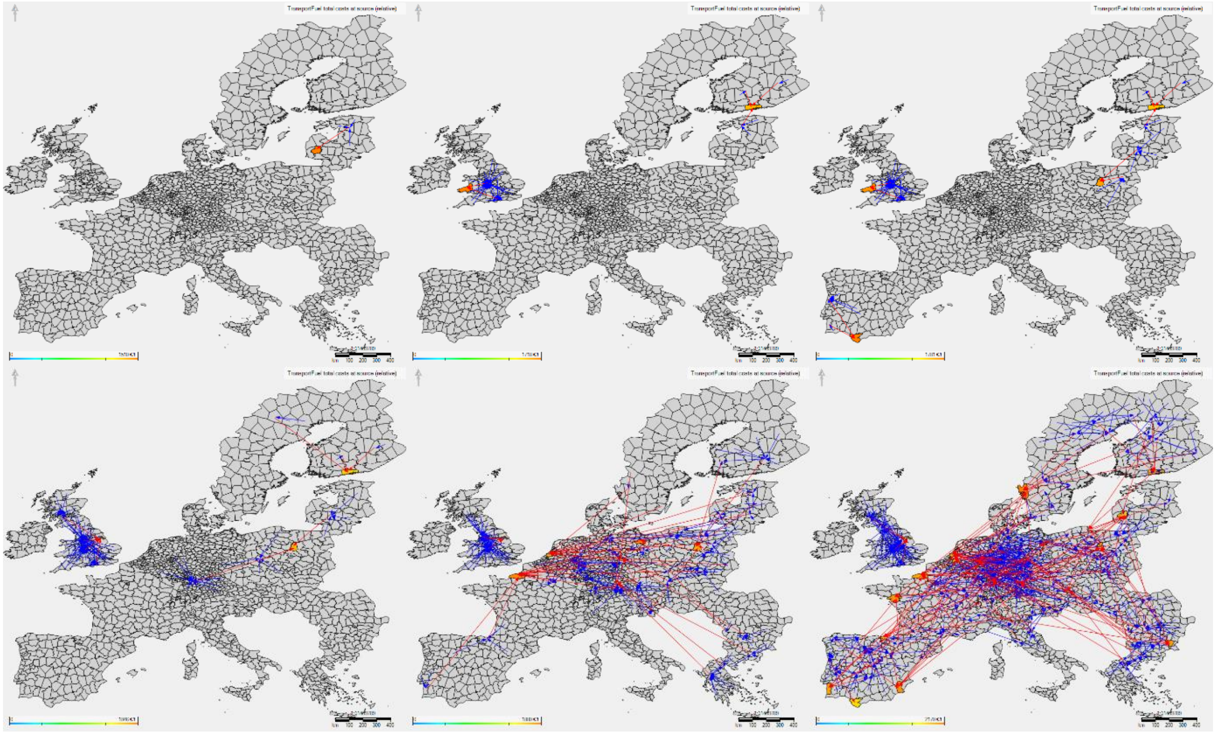

Figure 21 Successive Ramping Up

When using a different optimization strategy (NSGA II), where two objectives are considered at the same time, the result is a set of solutions that constitute good compromises between the objectives. In our case these objectives are transport fuel amount and relative production cost. As can been seen in Figure 21, this yields a succession of possible scenarios, starting with only the most profitable location and ramping up towards increased fuel production.

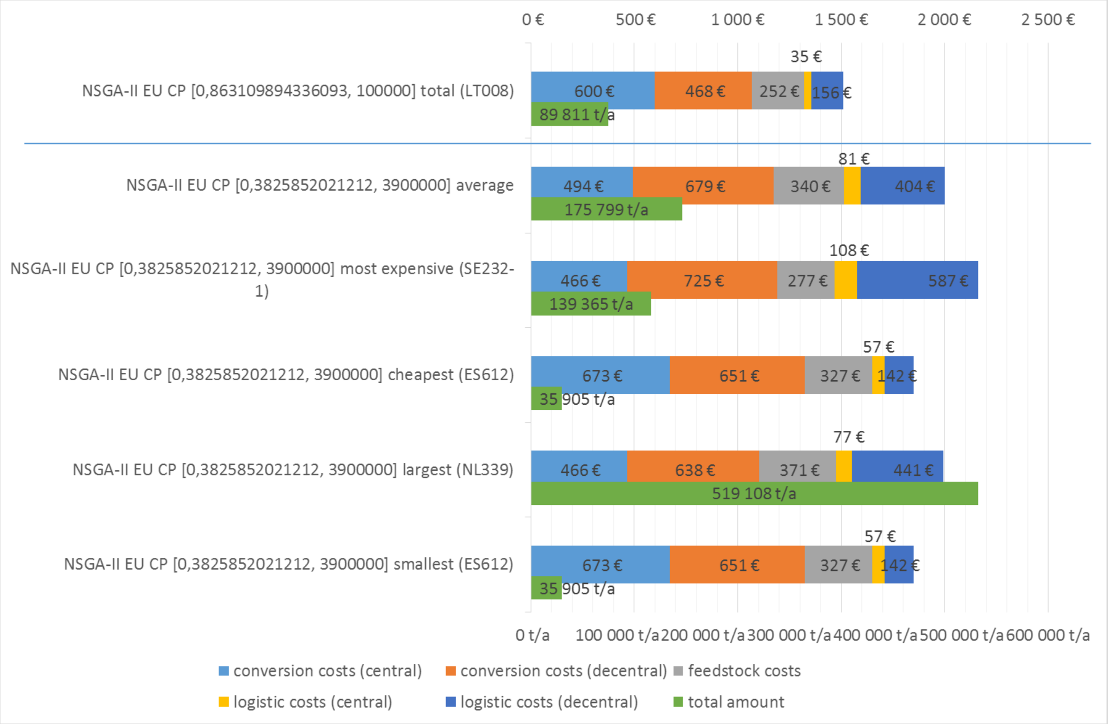

Figure 22 Comparison of Initial Plant vs. Ramp Up

Figure 22 shows a comparison between the solution with only the most profitable plant at the top and the ramped up scenario with almost 40 times the yield. For the ramped up scenario even the cheapest plant is less profitable than the single most profitable plant. Even though the initial scenario found with this strategy is better, the quality of the ramped up situations is inferior because the same optimization effort has now been split on a whole array of solutions instead of a single direction. In summary, these results show a complete estimate over the whole value chain for the production cost of catalytic pyrolysis biofuel.

9 Conclusions and Summary

In the following sections we summarize the main findings of WP4 which is focused on logistics optimization.

Our analysis of the costs for transport and handling of straw bales shows that transport with a truck with a draw-bar trailer in combination with a front-end loader for loading and a telescopic handler for unloading is one of the most viable options. A gantry crane should be used for handling of straw planes at the plant.

For the transport and handling of forestry residues as bundles the recommended transport vehicle is a timber truck in combination with a truck-mounted crane for loading and a telescopic handler or the truck mounted crane for unloading. A telescopic handler should be used for handling of forestry residue bundles at the plant. Alternatively, a screw conveyor should be used for chipped forestry residues.

The transportation and handling of municipal biodegradable waste has not been elaborated in detail as we assume that a form of collection infrastructure for this kind of biomass is already in place.

Concerning logistics of energy intermediates the analysis shows that transport by train with tank wagons is the most viable option for transport of pyrolysis oil. Transportation of the wet filter cake produced in the HTC process has not been elaborated in detail.

The main findings from the development of the simulation and optimization software component are concerned with technical design decisions.

We found that it is crucial to design the simulation model in a way to reduce the computational effort as much as possible to facilitate the optimization process. Reducing the simulation runtime has direct effect on the achievable solution quality in the optimization process because more potential solutions can be evaluated. We found that in the case of the BioBoost scenarios it is possible to improve efficiency of the simulation model by only considering yearly averages or aggregates and by limiting the number of options that are available in the simulation model (e.g. by assuming that all feedstock acquired in one region has to be transported to the same plant).

Retrospectively, it was important that we used a generic design for the simulation model which allowed us to easily adapt the steps in the value chain through a configuration file. This allowed us to iterate quickly to detect and remove bugs in the simulation model and to adapt the model quickly when new information on the conversion processes was received.

An important design decision for the development of the optimization model was that instead of optimizing plant locations and capacities directly in combination with the transport network the plant locations and capacities are only determined indirectly. Instead we introduced regional feedstock utilizations as variables and optimized these utilizations in combination with the transport network. The plant locations and optimal capacities are an indirect result of the feedstock utilizations and transport targets in the BioBoost optimization model. The benefit of this approach is the size of the solution space is reduced because many infeasible solutions are excluded from the new solution space and therefore optimization can be performed more efficiently.

Another important finding in the development of the optimization model was that it was necessary to support different optimization objectives. Initially, we started out with the objective to maximize the profits gained from the production of transport fuel, synthetic gas, or heat and power. When scenarios are optimized with this objective there are two possible results; if the overall production costs are below the revenues then the optimization algorithm will produce solutions where plant capacities are maxed out trying to produce as much final product as possible. However, if it is not possible to find scenarios where the overall production costs are smaller than the revenues then the optimal solution is to produce nothing at all because any operation would automatically incur a loss.

Therefore, we decided to allow optimization of the relative costs for the production of transport fuel, syngas, or heat and power through the BioBoost processes. Optimization of this objective allows us to identify and analyse the most cost effective scenarios, to answer such questions as “At which locations would it be most cost effective to operate de-central and central plants and from which regions should the biomass be sourced?”. This approach however has the drawback that optimization produces only the most cost effective plant and does not consider the amount of final products at all. An important conclusion therefore was that it must be possible to optimize two objectives (1) the final product amounts and (2) the relative production costs simultaneously to support analysis of technology ramp-up options. We found that the NSGA-II algorithm can be used to solve this multi-objective optimization goal.

For the single-objective optimizations we found that evolution strategies performed best. However, it is absolutely essential that semantic evolutionary operators are used which take the locations of plants and the transportation network for a plant into consideration when producing new solution candidates. Standard operators from literature such as single-point crossover or single-point mutation are not effective and lead to sub-optimal solutions. Experiments with several improved variants of genetic algorithms did not result in significantly better results than results produced with evolution strategies.

An unexpected finding in our optimization runs was that the plant size scaling factors have a strong effect on the optimal transport network. In BioBoost we consider scaling factors for the costs for larger plants to model relative decreases in costs for larger plants because of better efficiency. Optimization experiments showed that this scaling effect is very strong and combined with relatively low contribution of logistics cost has the tendency to produce very large plants. After the introduction of maximum capacities of plants we found that optimization usually finds solutions with plants at maximum capacity because the scaling effect is stronger than the opposing effect of longer transports and higher feedstock prices because of higher utilizations.

This effect is also especially apparent for optimal scenarios identified for catalytic pyrolysis plants where we assume that the biooil can only be further processed in existing refineries. Because of the beneficial scaling factor the assumed free capacities of refineries are maxed out and frequently if the nearest refinery for a de-central plant is already maxed out the transport is diverted to any other refinery because the transport costs for biooil are relatively small and outweighed by the scaling effect.

Finally, we several constraints had to be introduced into the simulation model in order to produce an accurate model. The constraints include maximum transport distances, minimum transport amounts, minimum plant capacities, maximum plant capacities and minimum utilizations. All these constraints are treated as soft constraints in the optimization procedure. When a solution is produced that violates any of these constraints a penalty is added to the objective value. We found that this is beneficial for the convergence of the optimization procedure and that careful balancing of these constraints is necessary.

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