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Brno University of Technology

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Marek Vondra*, Michal Touš, Sin Yong Teng

Brno University of Technology, Institute of Process Engineering & NETME Centre, Technická 2896/2, 616 69 Brno, Czech Republic, m.vondra@vut.cz

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Highlights

- Techno-economic assessment for integrating evaporators in biogas plants.
- Rigorous Monte Carlo simulations were carried out for liquid digestate modelling.
- Artificial Neural Network is used to prioritize variables in decision making.
- Decision trees are used to search for favourable decision pathways for the industry.
- Having CHP bonus would improve the scenario for industrial digestate thickening.

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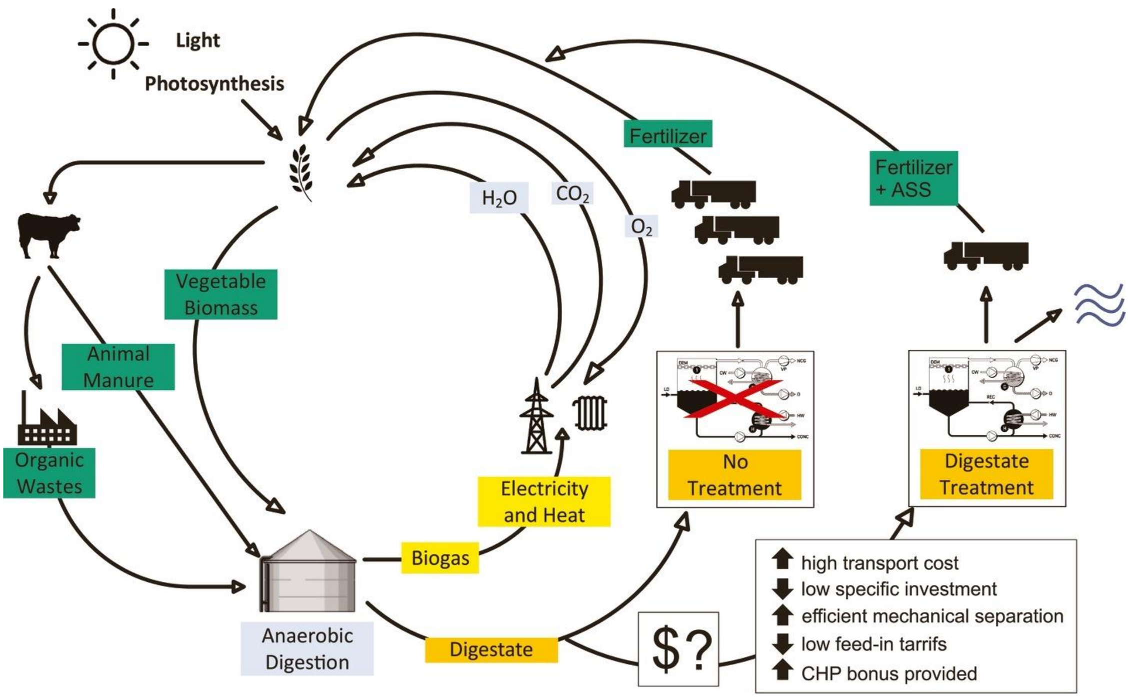
Keywords: Anaerobic Digestion; Machine Learning; Vacuum Evaporation; Liquid Digestate; Biogas Plant; Energy Consumption; Nutrient Recovery; Circular economy; Ammonium sulphate solution

Abstract

Biogas production is one of the most promising pathways toward fully utilizing green energy within a circular economy. The anaerobic digestion process is the industry standard technology for biogas production due to its lowered energy consumption and its reliance on microbiology. Even in such an environmental-friendly process, liquid digestate is still produced from the remains of digested bio-feedstock and will require treatment. With unsuitable treatment procedure for liquid digestate, the mass of bio-feedstock can potentially escape the circular supply chain within the economy. This paper recommends the implementation of evaporator systems to provide a sustainable liquid digestate treating mechanism within the economy. Studied evaporator systems are represented by vacuum evaporation in combination with ammonia scrubber, stripping and reverse osmosis. Nevertheless, complex multi-dimensional decisions should be made by stakeholders before implementing such systems. Our work utilizes a novel techno-economics model to study the techno-economics robustness in implementing recent state-of-art vacuum evaporation systems with exploitation of waste heat from combined heat and power (CHP) units in biogas plants (BGP). To take into the account the stochasticity of the real world and robustness of the analysis, we used the Monte-Carlo simulation technique to generate more than 20,000 of different possibilities for the implementation of the evaporation system. Favourable decision pathways are then selected using a novel methodology which utilizes the artificial neural network and a hyper-optimized decision tree classifier. Two pathways that give the highest probability of providing a fast payback period are identified. Descriptive statistics are also used to analyse the distributions of decision parameters that lead to success in implementing the evaporator system. The results highlighted that integration of evaporation system are favourable when transport costs and incentives for CHP units are large and while feed-in tariffs for electricity production and specific investment costs are low. The result of this work is expected to pave the way for BGP stakeholders and decision makers in implementing liquid digestate treating technologies within the currently existing infrastructure.

Graphical Abstract



1. Introduction

Biological processes have the inherent characteristics of preserving resources at a low cost and eco-friendly manner (Liguori and Faraco, 2016). One of the most attractive sources of energy from biological processes is the anaerobic digestion process (Ragazzi et al., 2017). It can effectively convert organic waste to biogas and can serve as a sustainable decentralised energy source even in developing countries (Azouma et al., 2018). The current boom of biogas plants (BGP) in Europe has led the Union to produce 61 TWh of electricity and 26.6 PJ of heat in the year 2015 (Scarlat et al., 2018). The ecosystem is causing biogas processing facilities to rapidly shift towards a circular economy (Fagerström et al., 2018). Biogas processing plants produce a large amount of leftover of digestate by-products from the bioreactor that must be properly processed (Al Seadi et al., 2013). This is a critical issue for sustainability development, as bio-resources can potential "escape" from the circular economy, giving net waste generation. Venkata Mohan et al. (2016) discussed that the utilisation of bio-waste as renewable feedstock can provide potential in developments towards the circular economy by enhancing bio-refinery competitiveness and social acceptance.

Anaerobic digestion is the industrial standard biogas production method. Waste biomass such as animal manure and crops are collected and fed to the anaerobic bioreactor. The slurry of biomass feedstock is digested by anaerobic microorganisms to produce biogas. In order to maintain a stable and high-quality biogas production, the feedstock's C/N ratio is ideally between 20-30 (Gómez et al., 2006). It was also reported that an increasing amount of long-chain fatty acid will also cause the flocculation of biomass and act as inhibition (Dasa et al., 2016). The sensitive nature of the anaerobic digestion process has encouraged many innovations in the research field, leading to the development of multiple types of bioreactors. Uçkun Kiran et al. (2016) stated that bioreactor configuration should depend on the solid content of feedstocks, where low solid content bioreactor includes anaerobic lagoons, completely mixed reactors, anaerobic filter reactors, fluidized bed reactors, upflow anaerobic sludge blanket reactors, anaerobic baffled reactors and membrane reactors. The work also recommended plug flow reactors, completely mixed reactors and contact reactors for medium solid content; while plug flow, completely mixed and leach-bed reactors can be used for high solid content feedstock. A review from Zhang et al. (2016) has shown that the research for anaerobic digestion has blossomed beautifully, covering detailed research on substrate analysis, pre-treatment, bioreactor configuration, operation and system analysis.

On the other hand, the fast-growing anaerobic digestion industry has opened new opportunities for digestate utilisation (Monlau et al., 2015). The work studied the possibility of digestate utilisation by algae cultivation, energy production using biological or thermal process and pyrolysis. Works of Fuchs and Drosg (2013) even refers to digestate utilisation as the bottleneck of the biogas industry (see Figure 1). They concluded that digestate processing plant of European countries such as Austria, Germany, Switzerland and Italy require an appropriate method for disposal of residue digestate. The industrial development of digestate to produce highly enriched nutrient was also recommended (Fuchs and Drosg, 2013). Life-cycle assessment of biogas production carried out by Berglund and Börjesson (2006) concluded with a set of transportation distance limits for different raw material to prevent negative energy balance. This indicates that dewatering (to reduce transportation load) is crucial in maintaining the net energy gain within the circular economy.

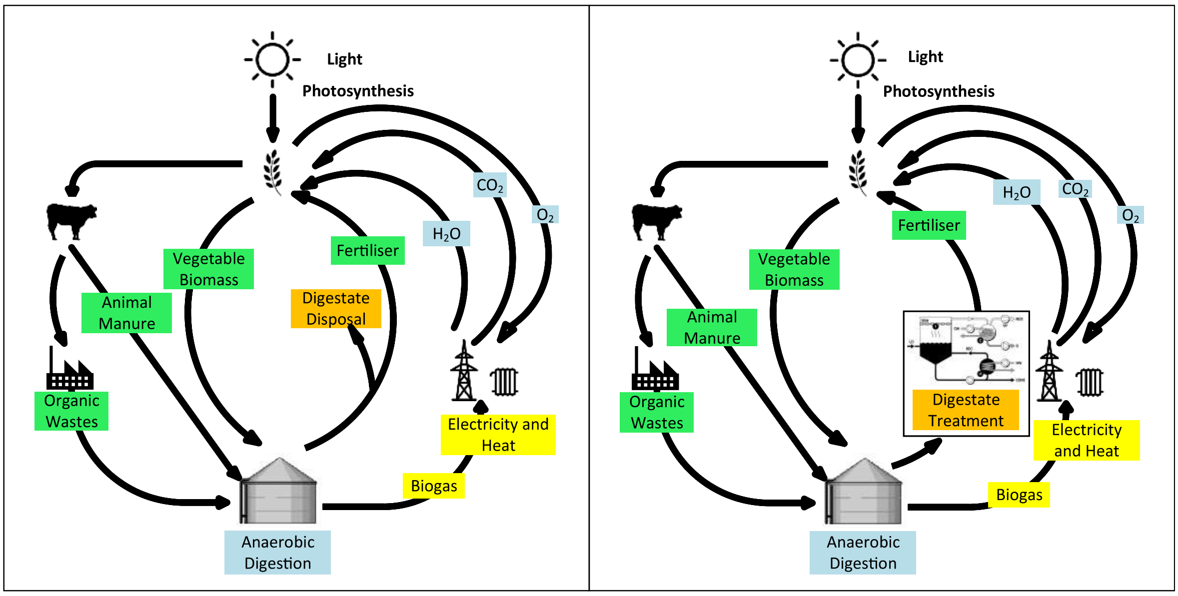


***Figure 1:** Digestate Treatment and the Circular Economy of Biogas Industry*

Kirchherr et al. (2017) conceptualized the circular economy with core principles of the 4R framework (Reduce, Reuse, Recycle and Recover), waste hierarchy and system perceptive. Key strategies to achieve circular economy from the linear economy are proposed to include creating useful applications of materials, extending the lifespan of products and parts, innovating smarter product use and manufacturing (Potting et al., 2017). In this context, the digestate by-products can be treated and transformed into bio-resources that are able to contribute in the soil, horticulture, renewable energy and bio-products within the circular economy (van Haeff, 2015). To accelerate this progress, encouraging efforts have been carried out by the European Commission in terms of funding for environmental and circular economy research (European Commission, 2019a). In the European Union, biogas factories are actively transitioning to complete the circular economy by improving the digestate treatment process (Fagerström et al., 2018). From a techno-economical viewpoint, integration of digestate treatment is not always feasible for all BGPs (Vondra et al., 2018b), more industrial incentives are required to make the project favourable by industry players and stakeholders.

The design of digestate treatment system is technically challenging and requires multiple dimensions of considerations. A recent review (Monfet et al., 2018) concluded that there are 14 possible categories of processes for digestate treatment. Those 14 processes are: thickening, dewatering, membrane filtration, struvite precipitation, ammonia stripping, ammonia oxidation, microwave radiation, pH adjustment, chemical hydrolysis, thermal drying, combustion, pyrolysis, gasification and ultrasound. Vaneeckhaute et al. (2017) shown that matured nutrient recovery technologies for digestates include phosphorus crystallization or extraction, ammonia stripping, acid air scrubber, membrane filtration, ammonia/phosphorus sorption, macrophytes or microalgae production and evaporation. The selection decision of these processes can be carried out with decision tools such as Biomethane-Calculator (Miltner et al., 2013) and CDPQ Decision Tools (2018). Works of Rehl and Müller (2011) also shown a comprehensive life cycle assessment comparison of biogas digestate processing technologies that can be used for process selection. Tampio et al. (2016) demonstrated that an approach of mass, nutrient and energy balance can be applied to digestate treatment systems. These methods can only select the category of which process to be used. Much more research and industrial experience are required to implement the correct system design. Significant works from various authors and their contribution to the current digestate treatment research can be found in Table 1 below:

Table 1: Significant works for the development and implementation of digestate treatment technologies

Work	**Contribution**
Chen et al. (2009)	Highlighted ecological and environmental protection type disposal of anaerobic digestate for large-scale BGPs.
Fuchs and Drosg (2013)	Conveyed the development in state-of-art industrial-scale technologies. Shown that industrial applicable technologies mainly consists of a combination of membrane treatment, evaporation and stripping technologies.
Al Seadi et al. (2013)	Proposed that digestate quality can be affected by feedstock of anaerobic digestion and shown that consideration of such variability is critical.
Golkowska et al. (2014)	Compared the treatment costs of four different digestate treatment technologies. Focused mainly on drying, pelletizing, reverse osmosis and denitrification.
Guercini et al. (2014)	Exploited the excess heat within the combined heat and power (CHP) unit of a BGP to a single-effect vacuum evaporator.
Koszel and Lorencowicz (2015)	Highlighted the use of biogas digestate as a replacement for agricultural fertilizer.
Dahlin et al. (2015)	Discussed the importance and barriers of marketing digestate products from a qualitative perspective.
Vondra et al. (2016)	Compared various designs of vacuum evaporators for the application of digestate treatment. Highlighted that multi-stage flash vacuum evaporator performs most efficiently.
Xia and Murphy (2016)	Demonstrated a front-end research on utilizing microalgae cultivation in treating liquid digestate from biogas systems.
Hung et al. (2017)	Front-end research demonstrating that treated digestate can be converted into valuable material such as biochar. Demonstrated the future possibilities of digestate-derived products.
Vondra et al. (2018b)	Proposed the integration of multi-stage flash vacuum evaporator in a BGP to exploit the excess heat within CHP unit.
Bolzonella et al. (2018)	Re-emphasized the importance of digestate treatment with estimated costs for non-vacuum dryers, stripping and membrane technologies.

For liquid digestate (LD) treatment using dewatering methodologies, our previous work (Vondra et al., 2016) has demonstrated the technical potential of LD thickening with the considerations of multiple industrial-standard evaporator systems. Chiumenti et al. (2013) tested the effectiveness of a two-stage configuration vacuum evaporator pilot plant in a 1 MWe anaerobic plant. The work studied the temperature, pH, total solid, volatile solids, total Kjeldhal nitrogen and acid consumption of the evaporation process. Full-scale evaporator plant is estimated to have energy consumption at 5-8 kWhe/m^3 of digestate and 350 kWht/m^3 of evaporated water (Chiumenti et al., 2013). A case study in Croatia has shown the high energy potential of treated digestate (Đurđević et al., 2018), which can be achieved using evaporation methodologies. This solution was also implemented in France where a 23,000 ton/year digestate evaporation plant was commissioned (Bamelis et al., 2015), showing that evaporation methodologies have become the industrial standards for digestate treatment. In our recent work, we studied the techno-economic assessment of integrating a novel vacuum evaporator into a conventional BGP (Vondra et al., 2018b). From that work, we concluded that the design decision and consideration of integrating the evaporator in a BGP can vary for each situation. As in any industrial processes, new technologies must be considered in terms of energy intensity, environmental impact, and financial aspects (Máša et al., 2013). Economic feasibility of integration depends on many factors. Besides the investment cost, it is digestate transport and application cost, dry matter content in liquid digestate, energy consumption of an evaporator system and many others. This paper will guide the reader on the implementation of evaporator systems based on the criteria in the BGP.

The main objective of this work is to analyse the integration of an evaporation technology for digestate treatment into BGP regarding investment. The analysis provides important results subsequently used in a tool to support decision making on investment. The tool is developed for BGP owners to make decisions on investing in evaporator technology. For this purpose, a complex mathematical model is presented and rigorous simulations (possible scenarios) for large range of inputs are analysed. As a secondary objective, the study aims to investigate the significance of individual inputs in terms of the overall payback period of the project. The novelty of this work is that it analyses the implementation of current state-of-art industrial-scale digestate treatment technologies (evaporation systems). As the implementation of such technologies requires complex multi-dimensional considerations (Monfet et al, 2018), a novel techno-economic assessment methodology is introduced which utilizes Monte-Carlo sampling, artificial neural network (ANN) and hyper-optimized decision tree to search for the optimal policies and scenarios to implementing such technologies.

2. Methodology

2.1. Introduction

The methodology and scientific procedure of this study are shown in Figure 2. Individual steps are described in the text below. At first, the BGP system was studied and clearly defined (Chapters 2.2, 2.3). Based on this definition, an analytical steady state techno-economic model was established (Chapter 2.4) and crucial input variables for further detailed research were identified. A thorough survey has revealed relevant ranges of values for particular operational variables (Table 2), which could occur in practice. Since there are no typical individual values which could be representative for a significant number of plants, we have decided to generate combinations of variables within allowable ranges. In this way, it was possible to simulate and analyse a large number of operating states that could appear in real BGPs.

Two procedures for the generation of particular values of given variables were subsequently defined. During the “no-rules based” procedure, input variables could reach any value within the given range. The “rules-based” procedure introduces restrictions, which do not allow certain combinations of variables to enter the model since their appearance in a real BGP is improbable. Both procedures implement the Monte Carlo simulation method for the generation of datasets and are thoroughly described in Chapter 2.5. Each dataset represents a particular scenario (Base cases, “CHP bonus“, “No ASS sale”) which are also defined in Chapter 2.5. The aim of the subsequent data analysis was to provide support for decision making (decision analysis) and to identify trends for technology implementation (exploratory data analysis).

2.2 System description

This study considers a typical agricultural BGP, which processes different biomass substrates for biogas production and subsequent heat and electricity generation. A major part of the electricity, not consumed by the BGP itself, is sold to the power grid and represents the main source of income. The produced heat is partly supplied to digesters for the anaerobic fermentation process, eventually to other thermal appliances (e.g. drying). In most cases, the produced heat is not fully utilized (Guercini et al., 2014) and needs to be wasted by air-cooled chillers to ensure a sufficiently low temperature of the recirculating cooling water. Digestate serves as valuable fertilizer, but its storage and transportation are associated with significant costs for operators. To save storage capacities, digestate is often subjected to mechanical separation, which reduces the volume of liquid fractions that needs to be stored in specialized tanks. However, the overall volume of fertilizer (liquid + solid fraction) stays the same.

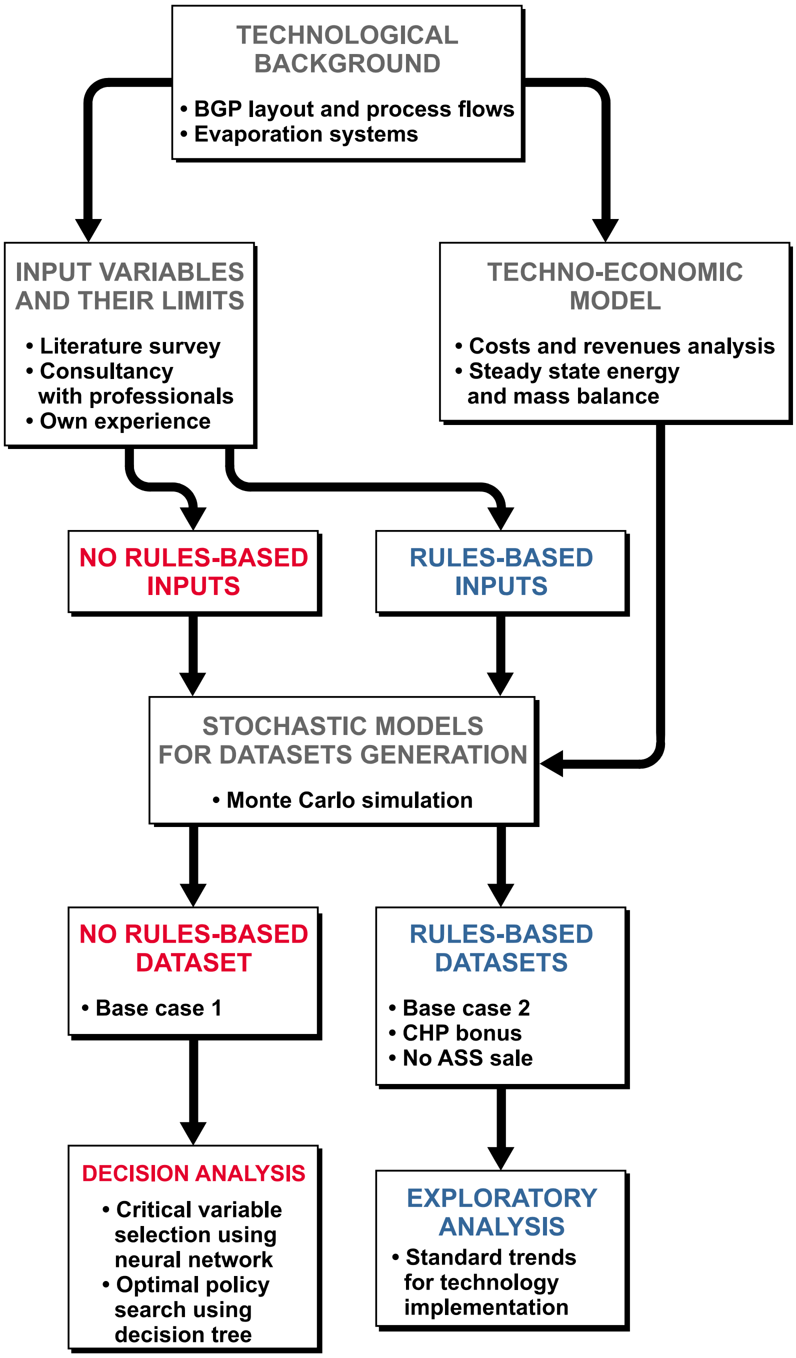


Figure 2: *Scientific procedure of this study.*

For further treatment of LD, which could take up to 90 % of the original digestate volume, we assume the integration of an evaporation system. For the purpose of this study, we define evaporation system (ES) as a processing unit that: 1) contains a vacuum evaporator (VE), 2) reduces LD volume and at the same time preserves its fertilizing potential, 3) can produce clean water suitable for discharge into the environment, i.e. is able to prevent ammonia from entering the outgoing freshwater stream. Considered ESs are visualized in Figure 3.
Each ES (A, B, C) produces two output streams during the vacuum evaporation – concentrate (thickened LD) and ammonia water. The degree of volume reduction of LD differs with the efficiency of VE and with input parameters of LD. Higher the input dry matter (DM) content, lower the potential for volume reduction. The concentrate contains most of the original nutrients. The only serious but major loss is dedicated to ammonia, which volatilizes during the evaporation step. This could be partially avoided by pH modification, using sulphuric or nitric acid. The dosage of acid depends on the concrete strategy for the ES operation and could be omitted. The operation of VE could also require the addition of a certain anti-foaming agent, since LD is prone to foaming.
In the case of ES (A), presented by Maier (2018), ammonia and water are leaving the VE in gaseous form and are entering the scrubber where the ammonia is reacted with sulphuric acid, forming ammonium sulphate. Since the

reaction is exothermic, the scrubber can prevent most of the water from condensing. The small portion of condensed water leaves process together with ammonium sulphate in the form of ammonium sulphate solution (ASS). This valuable by-product has the potential to be sold as a fertilizer and contribute as a possible secondary income for BGP owner. Alternatively, ASS could be used for standardization of nitrogen content in the concentrated LD. Condensation of the rest of the water vapour takes place right after the scrubber. Produced water should reach the required quality for discharge.

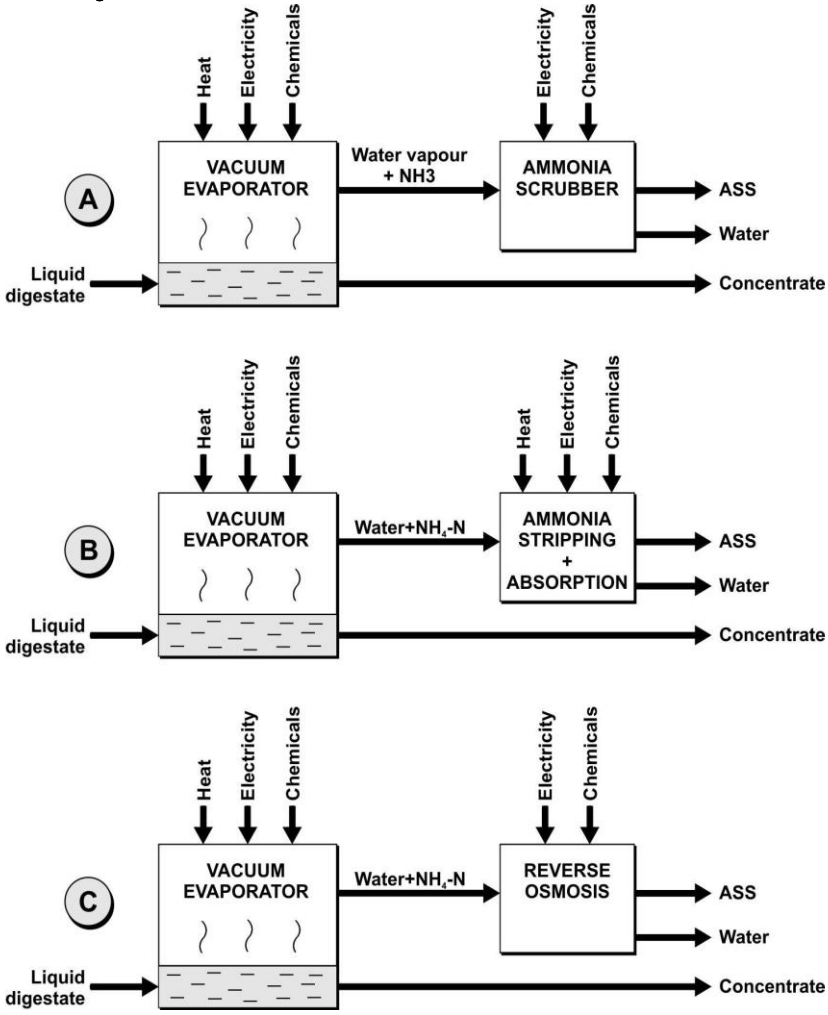


Figure 3: *Considered evaporation systems for the liquid digestate treatment. ASS = Ammonium sulphate solution*

Systems (B) and (C) need to deal with the liquid ammonia-water solution that is produced during condensation in the VE. In the ES (B), stripping with the subsequent absorption of ammonia in sulphuric acid is considered. This system was studied by (Melse and Verdoes, 2005). Increase in temperature and pH (e.g. with sodium hydroxide) of the solution are favourable for ammonia release during the stripping process, hence the heat consumption of this system could be higher in comparison with systems (A) and (C). If there is enough waste heat available, this disadvantage does not apply.

A different approach for ammonia recovery is proposed in the system (C). The ammonia-water solution with decreased pH (using e.g. sulphuric acid) is treated with the reverse osmosis. Separated water could be eligible for discharge. The retentate (low concentrated ASS) could be subsequently thickened back in the VE, or directly stored for further use. This system was referred to by Bamelis et al. (2015).

2.3 Scope of Study

This paper and its results are valid only for a given set of BGPs which comply with the following assumptions:

a) Prior to entering ES, the digestate is treated by a suitable mechanical separator (e.g. screw press, decanter centrifuge), thus the LD is free of large solid particles and fibrous material.

b) There is no extra heat available from external sources. If so, it is not considered.

c) There are no legal restrictions on the proposed digestate processing and its subsequent utilization as a fertilizer.

d) There is no further processing of products and associated extra revenues from these activities (e.g. drying and pelletizing of concentrated LD, advanced methods for nutrient recovery).

e) The storage of concentrated LD, its transportation and application on a field are technically feasible with current machinery and equipment, there is no need for further investments in this regard.
f) Costs associated with increased safety requirements for the storage of auxiliary chemicals are negligible.
g) The technological layout and process flows of investigated BGPs are in compliance with Fig. 4.

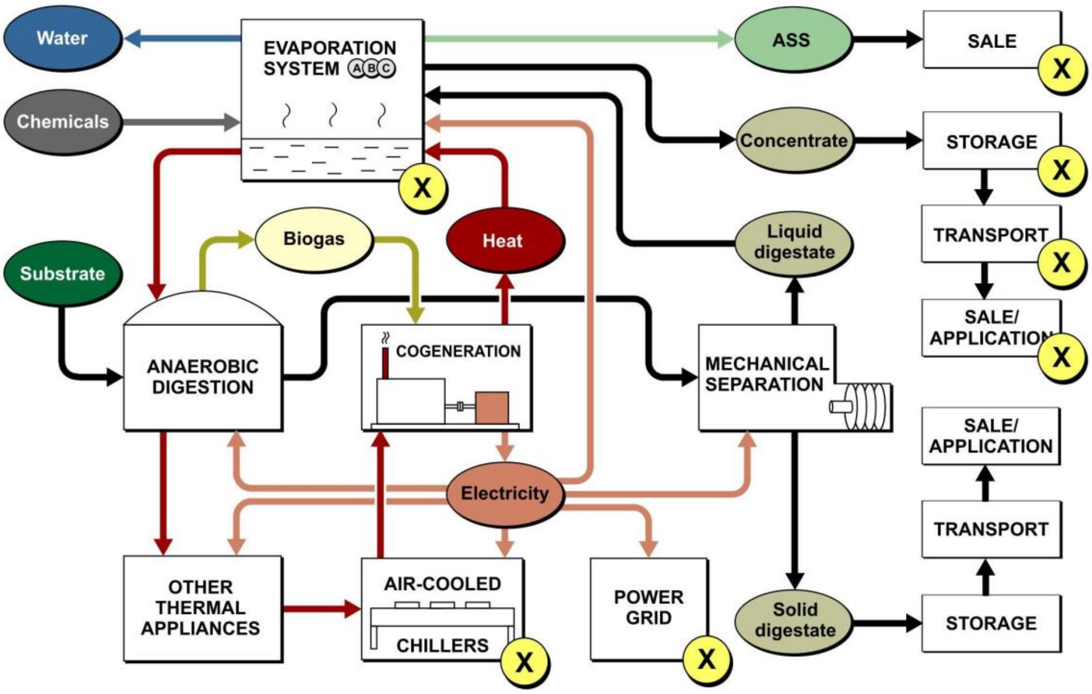


Figure 4: *Technological layout and basic process flow diagram of the considered biogas plant. The "X" denominates process units and operations whose economy will be affected by the integration of suitable evaporation system.*

2.4 Techno-economic model

The techno-economic model considers only those process units and operations, whose economy will be affected by the integration of ES. These units and operations are marked in Figure 4 and their influence on costs and revenues is described in more detail in the following paragraphs. The techno-economic model was built on the basis of the presented mathematical relations, using MS Excel 2013 and VBA programming language. The model is steady state, analytical and is governed by energy and mass balance throughout the BGP.

2.4.1 Payback period

Simple payback period (PP) was selected as the main criterion for the feasibility evaluation. The zeroth year of the payback period is defined as the exact time of digestate treatment technology being commissioned in the BGP. The payback period is dependent on investment costs and a change in the cash flow ($\Delta REV - \Delta CTS$), where the change is a direct result of the integration of an ES. Payback period was calculated in accordance with Eq. (1).

$$PP = INV/(\Delta REV - \Delta CTS) \qquad (1)$$

The overall change in revenues (Eq. (2)) is represented by the change in revenue from electricity sale (ΔREV_{el}^{sale}), change in revenue from the sale of concentrated LD (ΔREV_{conc}^{sale}) and by newly acquired revenue from ASS sale (REV_{ass}^{sale}). The overall change in costs (Eq. (3)) is represented by the change in costs for LD transport (ΔCTS_{ld}^{tran}) and by costs connected with the newly integrated ES, i.e. costs for chemicals consumption (CTS_{evap}^{chem}) and maintenance of the ES (CTS_{evap}^{mnt}).

$$\Delta REV = \Delta REV_{el}^{sale} + \Delta REV_{conc}^{sale} + REV_{ass}^{sale} \qquad (2)$$

$$\Delta CTS = \Delta CTS_{ld}^{tran} + CTS_{evap}^{chem} + CTS_{evap}^{mnt} \qquad (3)$$

2.4.2 Change in revenues from electricity sale

Electric power is the most valuable output of BGPs. Since most feed-in tariffs (also including premium tariffs which are driven by market prices) are subsidized, BGPs are trying to maximize their electric output, thus minimizing their internal consumption. The change in revenues from the electricity sale comprises of two parts (Eq. (4)) – change in revenue from the net electricity production and optional extra income from the CHP generation.

$$\Delta REV_{el}^{sale} = sPE_{fit} \cdot SH \cdot \left(\Delta PC_{ac}^{el} + \Delta PC_{agit}^{el} - PC_{evap}^{el}\right) + sPE_{chp} \cdot SH \cdot PO_{cog}^{el}/1000 \tag{4}$$

Table 2: *Considered variables, condition and limits.*

Input variable	Nomenclature	Units	Min	Max	Based on
Electricity feed-in tariff	sPE_{fit}	EUR kWh^{-1}	0.06	0.25	Pablo-Romero et al. (2017)
Specific costs for LD application	$sCTS_{ld}^{apl,var}$	EUR m^{-3}	1	5	Auburger et al. (2015), Drosg et al. (2015), Author's databank*
Maintenance coefficient	k_{evap}^{mnt}	-	0.05	0.15	Author's databank*
Specific price of chemicals	sP_{chem}	EUR t^{-1}	0	4	Author's databank*
Specific costs for LD transport	$sCTS_{ld}^{tran,var}$	EUR m^{-3}	2	12	Auburger et al. (2015), Drosg et al. (2015), Author's databank*
Installed electrical power output	PO_{cog}^{el}	MW	0.05	3	Scarlat et al. (2018)
Specific annual production of digestate	$sPRA_{dig}$	t y^{-1} MW^{-1}	10000	30000	CZBA (2014), Author's databank*
DM concentration in digestate	DM_{dig}	wt%	4	12	Monlau et al. (2015), Drosg et al. (2015), Author's databank*
DM concentration in LD	DM_{ld}	wt%	2	8	Møller et al. (2002), Drosg et al. (2015), Author's databank*
DM concentration in concentrate	DM_{conc}	wt%	8	15	Guercini et al. (2014), Drosg et al (2015), Author's databank*
DM concentration in solid fraction	DM_{sf}	wt%	20	35	Møller et al. (2000), Drosg et al (2015)
Specific thermal power consumption of evaporation system	$sPCM_{evap}^{th}$	kWh t^{-1}	150	500	Cordes (2018), Vondra et al. (2018a), Author's databank*
Specific electric power consumption of evaporation system	$sPCE_{evap}^{el}$	kWh t^{-1}	8	25	Cordes (2018), Chiumenti et al. (2013), Author's databank*
Coefficient of heat consumption	k_{bgp}^{th}	-	0.2	1	Daniel-Gromke et al. (2017), Author's databank
Specific power consumption of air-cooled chillers	$sPCE_{ac}^{el}$	kW MW^{-1}	5	15	Noel and Fourcroy (2017), Author's databank*
Change in specific power consumption of agitators	$\Delta sPCE_{agit}^{el}$	kW MW^{-1}	-3	6	Author's databank*
CHP bonus	sPE_{chp}	EUR kWh^{-1}	0	0.05$^{a)}$	European Commission, (2019b)
Specific production of ASS	$s\dot{M}_{ass}$	wt%	0.025	0.035	Maier (2018), Cordes (2018)
Specific market price for ASS	sP_{ass}^{sale}	EUR t^{-1}	10$^{b)}$	30$^{b)}$	Maier (2018)
Specific investment costs of a project	$sINV$	EUR y t^{-1}	10	40	Author's databank*
Thermal efficiency of cogeneration unit	η_{cog}^{th}	%	42$^{c)}$		Author's databank*
Electrical efficiency of cogeneration unit	η_{cog}^{el}	%	42$^{c)}$		Author's databank*
Service hours	SH	h y^{-1}	8760$^{c)}$		Author's databank*

Notes: *Author's databank: Own experience, consultancy with BGP operators and professionals from 2013 to 2019; a) Only in the "CHP bonus" scenario, otherwise without CHP bonus; b) Not valid in the "No ASS sale" scenario; c) Constant variables

The net electricity production will be affected by the power consumption of air-cooled chillers, agitators in storage tanks and the ES itself. The most important parameter regarding the electricity sale is the feed-in tariff (sPE_{fit}) for electricity production from biogas, which could differ based on a particular policy or government strategy. Based on the work of Pablo-Romero et al. (2017) we decided to place the value of sPE_{fit} in the range from 0.06 to 0.25 EUR kWh^{-1} (Table 2).

2.4.3 Change in power consumption of air-cooled chillers

The difference between the cooling performance of air-cooled chillers in the original BGP ($PC^{th}_{ac,orig}$) and after the ES integration ($PC^{th}_{ac,new}$) is equal to the thermal power consumption of the ES (PC^{th}_{evap}), Eq. (5). This is due to the fact that the evaporation technology basically acts as a sink for the waste heat. PC^{th}_{evap} is calculated (Eq. (5)) from the specific thermal consumption of the ES ($sPCM^{th}_{evap}$) and LD flow rate ($\dot{M}_{ld}$). $sPCM^{th}_{evap}$ was estimated from Vondra et al. (2018a) to range between 150 and 500 kWh/t. The change in electricity consumption of air-cooled chillers (ΔPC^{el}_{ac}, Eq. (6)) is also influenced by their specific electricity consumption ($sPCE^{el}_{ac}$), which could vary approx. between 5 to 15 W/kWh (Noel and Fourcroy, 2017).

$$PC^{th}_{evap} = PC^{th}_{ac,orig} - PC^{th}_{ac,new} = sPCM^{th}_{evap} \cdot \dot{M}_{ld} \tag{5}$$

$$\Delta PC^{el}_{ac} = PC^{el}_{ac,orig} - PC^{el}_{ac,new} = sPCE^{el}_{ac} \cdot \left(PC^{th}_{ac,orig} - PC^{th}_{ac,new}\right) \tag{6}$$

It must be added that in most cases, the evaporator itself requires a certain amount of cooling capacity, which could be satisfied in different ways (cooling towers, AC chillers, heat recovery etc.). For the purposes of this study, it is assumed that power and investment requirements for the cooling capacity are an implicit part of the overall technical specification and price of the ES.

2.4.4 Change in power consumption of agitators

Stored LD requires regular mixing to prevent solids from settling. If the digestate is currently stored in 2 or more tanks, it can be expected that after the thickening, fewer tanks will be used for storage and the total consumption of agitators will be reduced. If the digestate is stored in one tank only, the remainder after the thickening is stored again in this one tank, but consumption of agitators will increase as they will mix a thicker and more viscous suspension. Thus we expect that the change in specific power consumption of agitators ($\Delta sPCE^{el}_{agit}$) could be in a range from (-3,0) to 6 W per kW of electricity installed, where the negative value represents option with a single storage tank. The change in the power consumption of agitators (ΔPC^{el}_{agit}) is calculated according to Eq. (7).

$$\Delta PC^{el}_{agit} = \Delta sPCE^{el}_{agit} \cdot PO^{el}_{cog} \tag{7}$$

2.4.5 Power consumption of evaporation system

The overall electricity balance will be negatively influenced by the consumption of ES (PC^{el}_{evap}), which is determined using Eq. (8). Here the specific electricity consumption ($sPCE^{el}_{evap}$) and LD mass flow rate ($\dot{M}_{ld}$) are decisive factors. Based on works by Vondra et al. (2018a) and Chiumenti et al. (2013) we expect $sPCE^{el}_{evap}$ to vary between 8 and 25 kWh per tonne of LD treated.

$$PC^{el}_{evap} = sPCE^{el}_{evap} \cdot \dot{M}_{ld} \tag{8}$$

2.4.6 Mass balance

The production of digestate ($\dot{M}_{dig}$) could be estimated from installed power output of a BGP (PO^{el}_{cog}), number of service hours (SH) and specific annual digestate production ($sPRA_{dig}$), which is typically in the range from 10,000 m^3 to 30,000 m^3 per year and MW of electricity installed according to Eq. (9).

$$\dot{M}_{dig} = (PO^{el}_{cog} \cdot sPRA_{dig})/SH \tag{9}$$

Mass flows during the mechanical separation are governed by Eqs. (10) and (11). The production of LD could differ based on the separator type and its setup. It is supposed that the dry DM content in digestate (DM_{dig}) from wet anaerobic digestion could vary between 4 and 12 %, which is within boundaries set by Monlau et al. (2015) and Drosg et al. (2015).

$$\dot{M}_{dig} = \dot{M}_{ld} \cdot \dot{M}_{sf} \tag{10}$$

$$\dot{M}_{dig} \cdot DM_{dig} = \dot{M}_{ld} \cdot DM_{ld} + \dot{M}_{sf} \cdot DM_{sf} \tag{11}$$

Production of the concentrated LD ($\dot{M}_{conc}$) in the ES is governed by Eq. (12) under the assumption that all the DM stays in the concentrate. The final DM concentration (DM_{conc}) is an input provided by the technology manufacturer. We suppose DM_{conc} between 8 and 15 % as more concentrated DM would require demanding types of evaporators with stirrers. Production of fresh water ($\dot{M}_{fw}$) could be calculated using Eq. (13). Mass flow rates of applied chemicals are neglected.

$$\dot{M}_{ld} \cdot DM_{ld} = \dot{M}_{conc} \cdot DM_{conc} \quad (12)$$

$$\dot{M}_{fw} = \dot{M}_{ld} - \dot{M}_{conc} - \dot{M}_{ass} \quad (13)$$

The density of digestate and its fractions were estimated using Eq. (14), where the result is solely dependent on the DM content (DM) of a particular stream:

$$\rho_{dig} = 4.81 \cdot DM + 1026.2 \quad (14)$$

Hence the volumetric flow rate of digestate ($\dot{V}_{dig}$) and any of its fractions ($\dot{V}_{ld}, \dot{V}_{conc}$) can be calculated using Eq. (15):

$$\dot{V}_{dig} = \dot{M}_{dig} / \rho_{dig} \quad (15)$$

2.4.7 Change in revenues from the sale of concentrated LD:

Thickening of the LD increases its price as the final product contains almost the same amount of nutrients but in a much smaller volume. It is assumed that the increase in the price of the LD is directly proportional to the change in its volume ($\dot{V}_{ld} - \dot{V}_{conc}$) as the change of volume is directly proportional to the saving of application (spreading) costs. This could be beneficial both for the external end user of the fertilizer or for the plant operator himself, if he is the one who utilizes the LD for the fertilization of soil. Change in revenues (ΔREV_{conc}^{sale}) is determined using Eq. (16), where $sCTS_{ld}^{apl,var}$ stays for specific variable costs for the application of LD and are expected to range from 1 to 5 EUR/t.

$$\Delta REV_{conc}^{sale} = sCTS_{ld}^{apl,var} \cdot SH \cdot (\dot{V}_{ld} - \dot{V}_{conc}) \quad (16)$$

2.4.8 Revenues from the ammonium sulphate solution (ASS) sale:

The production of ASS will vary with the type of process unit (scrubber, stripper, reverse osmosis) responsible for the reaction between sulfuric acid and ammonia (NH_3) or ammonium (NH_4^+). Although the operation itself could be different, the overall mass flow rate of ASS produced will change only slightly, since the general requirement for ammonia removal is the same and is mainly driven by the terminal concentration of ammonia in the separated fresh water. The specific mass flow rate of ASS ($s\dot{M}_{ass}$) will be provided by technology supplier and is estimated between 25 and 35 kg/t of LD. The revenue from ASS sale (REV_{ass}^{sale}) could be calculated using Eq. (17). The market price for ASS (sP_{ass}^{sale}) may vary throughout the EU and will be influenced by demand and purchasing power of local companies.

$$REV_{ass}^{sale} = sP_{ass}^{sale} \cdot s\dot{M}_{ass} \cdot \dot{M}_{ld} \cdot SH / 100 \quad (17)$$

2.4.9 Change in costs for LD transportation

The volume reduction of LD in comparison with the original situation will affect transportation costs. Overall transport costs reduction (ΔCTS_{conc}^{tran}, Eq. (18)) will be proportional to the difference between the volumetric flow rate of LD after the thickening process ($\dot{V}_{conc}$) and the original one ($\dot{V}_{ld}$). Total savings related to LD transport are influenced by specific variable transportation costs ($sCTS_{ld}^{tran,var}$), which are strongly related to average transport distance. Since the transport distance can exceed 100 km in certain areas (North-West Germany), we may expect high fluctuation in $sCTS_{ld}^{tran,var}$ and therefore also in ΔCTS_{conc}^{tran}.

$$\Delta CTS_{conc}^{tran} = sCTS_{ld}^{tran,var} \cdot SH \cdot (\dot{V}_{conc} - \dot{V}_{ld}) \quad (18)$$

2.4.10 Costs for chemicals consumption

To reach a required quality of products using any type of proposed ES, utilization of certain chemicals is a must. Sulphuric acid is the cheapest solution (nitric acid as a more expensive option) for the ammonia recovery in ESs. Intensive foaming is typical for the evaporation of the LD, hence an antifoaming agent could be another chemical input consumed in the process. Specially modified evaporators are capable of zero AFA consumption, but higher investment or operational costs (e.g. for mechanical foam disruption) must be considered.

The overall consumption of chemicals could vary significantly based on the particular system configuration. To evaluate overall costs for chemicals consumption (CTS_{evap}^{chem}) according to Eq. (19), a technology supplier must provide information about the expected specific price of chemicals (sP_{chem}) per tonne of treated LD. This study assumes sP_{chem} to reach up to 4 EUR/t.

$$CTS_{evap}^{chem} = sP_{chem} \cdot \dot{M}_{ld} \cdot SH \quad (19)$$

2.4.11 Costs for technology maintenance

As any other process unit, even an ES will require maintenance throughout its lifetime. It will mainly require regular washout of its components, especially heat transfer surfaces and pumps, which could suffer from clogging and fouling. Occasional professional service or replacement of damaged components should also be expected. LD is an organic solution with high viscosity and significant content of DM and it is quite difficult to handle. Annual costs for technology maintenance (CTS_{evap}^{mnt}) could be estimated as a percentage from total investment costs (INV) and in the Eq. (20) are expressed by the maintenance coefficient (k_{evap}^{mnt}), which is estimated to range between 0.05 to 0.15.

$$CTS_{evap}^{mnt} = k_{evap}^{mnt} \cdot INV \quad (20)$$

2.4.12 Investment costs

For purposes of this study, total investment costs (INV of a project are calculated from specific investment costs ($sINV$) per tonne of processed LD. This approach allows comparison of BGPs with different capacities, which would vary significantly in terms of total investment costs. Eq. (21) describes the calculation:

$$INV = sINV \cdot \dot{M}_{ld} \quad (21)$$

2.4.13 Thermal energy consumption

For the thickening project to be successful, it is necessary to utilize only as much heat, as it is available in the BGP in a form of cost-free waste heat. Thermal energy is the main source of energy for the evaporation process. Any requirement for extra thermal energy production would significantly reduce the feasibility of the project, most probably it would make it unacceptable. In this study, the feasibility of the project considers the scenarios in which the evaporation system does not consume more than available amount of heat (this is considered as infeasible). This condition is described by Eq. (22), where PC_{bgp}^{th} refers to own heat consumption by the BGP. PC_{bgp}^{th} is determined in accordance with Eq. (23) and is dependent on the coefficient of heat consumption (k_{bgp}^{th}). In BGPs the heat is utilized for the digestion process, eventually for drying processes or heating of social buildings, stables, attached industrial or commercial premises etc (Daniel-Gromke et al., 2017). In certain cases k_{bgp}^{th} could reach up to 1, i.e. there is no available waste heat and evaporation project is rated as infeasible.

$$PC_{evap}^{th} \leq PO_{cog}^{th} - PC_{bgp}^{th} \quad (22)$$

$$PC_{bgp}^{th} = k_{bgp}^{th} \cdot PO_{cog}^{th} \quad (23)$$

Thermal power output of the cogeneration unit was determined using Eq. (24), where η_{cog}^{th} and η_{cog}^{el} are constants, both equal to 42 %.

$$PO_{cog}^{th} = PO_{cog}^{el} / \eta_{cog}^{el} \cdot \eta_{cog}^{th} \quad (24)$$

2.5 Datasets generation and analysis

As introduced earlier, there are two main outputs. Firstly, a support for decision making in a form of a decision tree, which was generated using a “no rules-based” dataset (Chapter 2.5.1). Secondly, exploratory data analysis was carried out to provide comprehensive information about feasibility of the system integration. “Rules-based” datasets were used (Chapter 2.5.2) for that purpose.

To the authors’ knowledge, there is no sufficiently extensive database of parameters of existing BGPs which could be used for the aforementioned analyses. So, to reproduce variability of real operational parameters, a stochastic approach was deployed to simulate datasets using the Monte-Carlo (MC) method together with the techno-economic model presented in Chapter 2.4. Each dataset is obtained by 20,000 simulation runs with randomly generated values of the independent variables. Each combination of variables represents the operational parameters of one particular BGP. We call these combinations as “samples”. The aim of the subsequent data analysis was to identify successful combinations of samples that are favourable for the economy of the project. Feasibility of the samples is tested using three criteria: consumed heat is lesser or equal to available heat, cash flow is positive and payback period is below certain level (3 or 5 years for “no rules-based”, 15 years for “rules-based datasets”). The samples, which do not meet these requirements, are not feasible. But they are not excluded from the results. They just represent the set of solutions which are not acceptable for BGP.

2.5.1 “No rules-based” dataset

For the decision analysis, it is necessary to have all combinations of values of the independent variables since PP is investigated as a function. The full decision space for the implementation of ES is generated by MC simulations of the rigorous techno-economic model. In the MC simulation, each point in the domain space is assigned an equal probability to give a non-bias decision space. We categorized this generated data set under “no rule-based” dataset and assigned the name “Base case 1” to this scenario. The parameters of the uniform distribution, minimum and maximum value, were estimated according to data found in literature or according to the authors’ experience or consultancies with technology suppliers and BGP operators (specified in the Table 2).

The tools used for the decision analysis are the Statistica package and development in Python 3.7. We extended development based-on conventional development libraries such as sklearn, matplotlib, scikit-optimize, dtreeviz, pyplotplus. The decision analysis aims to select important variables from a well-trained artificial neural network, then using them to train a decision tree classifier.

The decision tree classifier functions to separate sub-solution spaces of fast payback period (0-3 years) and medium payback period (3-5 years) from the full decision space. This approach is expected to give solutions that are more reliable and robust, as the optimality is not presented as a “point”, but as a solution space in the tree’s leaf node. The tree is pruned and validated with an alternative set of testing data. Bayesian optimization is also carried out to efficiently tune the hyper-parameters of the decision tree, ensuring no overfitting and high validation performance (see Figure 5).

Using 20,000 data points from Monte Carlo simulations, important significant variables were selected by using a simple artificial neural network with the automated search algorithm. The artificial neural network architecture was searched between 10 to 25 hidden layers and variable activation functions including Identity, Logistics, Hyperbolic Tangent and Exponential functions. Sensitivity analysis was carried out for each variable by turning off the respective variables in the neural network and measure the error in payback period prediction. If the shut-off variable causes a high error in prediction, it is higher in importance. The importance factor is shown in Eq. (25):

$$I(x_k) = \sum |y - y'(x_n)| \qquad where\ \forall n \in N, \qquad \mathrm{k} \notin N \tag{25}$$

The decision tree classifier was trained with a best split greedy approach by minimizing entropy at each resulting node. The entropy of the node is correlated with the probability of classes within the classification group (see Eq. (26)). This ensures that the information gain is maximized when moving down the tree. We also trained our decision tree with 20,000 Monte Carlo simulation data, while using a separate 20,000 Monte Carlo simulation points for validation.

$$Entropy = -\sum_j p_j \ log_2 p_j \tag{26}$$

A simple pruning algorithm was used to eliminate repeated classifications of the same class. Nevertheless, the pseudo-code for the algorithm is shown in Table 3 for easier understanding.

Table 3: *Algorithm for decision tree pruning*

Algorithm 1 Basic pseudo-code for decision tree pruning	
1: **Repeat**	
2: **For each** leaf nodes in decision tree **do**	*• Get the leaf nodes of tree*
3: Get parent of leaf node	*• Check the decision of the parent of tree node*
4: **If** classification of parent == classification of leaf **node**	*• Check if there are trivial leaf nodes*
5: Remove all child of parent **with** classification==parent	*• Remove trivial leaf nodes*
6: Update leaf nodes	*• Update the new leaf nodes after previous are removed*
7: **Until** all classification of leaf nodes != classification of parent	*• Repeat until no more trivial leaf nodes*

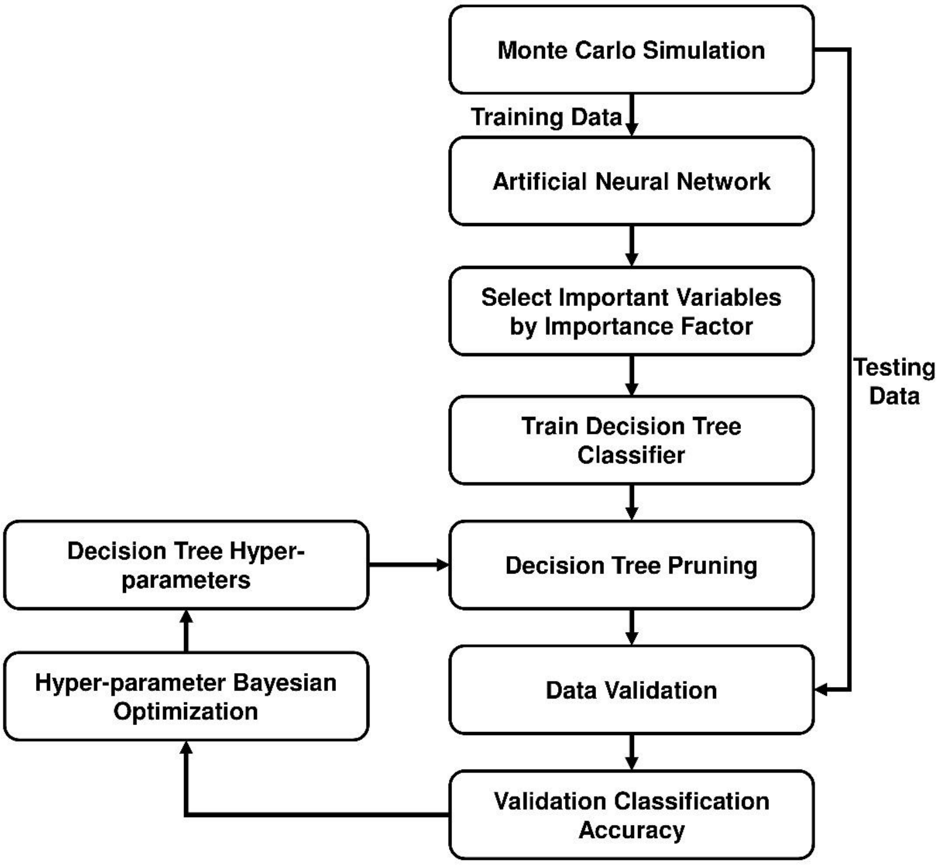


Figure 5: *Procedure for full decision space analysis*

The effects of this pruning algorithm allow the tree to have a reduced number of nodes while maintaining the same level of accuracy within the decision tree. This can be visualized in Figure 6, where two leaf nodes of the same classification were effectively pruned to form a tree with reduced branches but same classification accuracy.

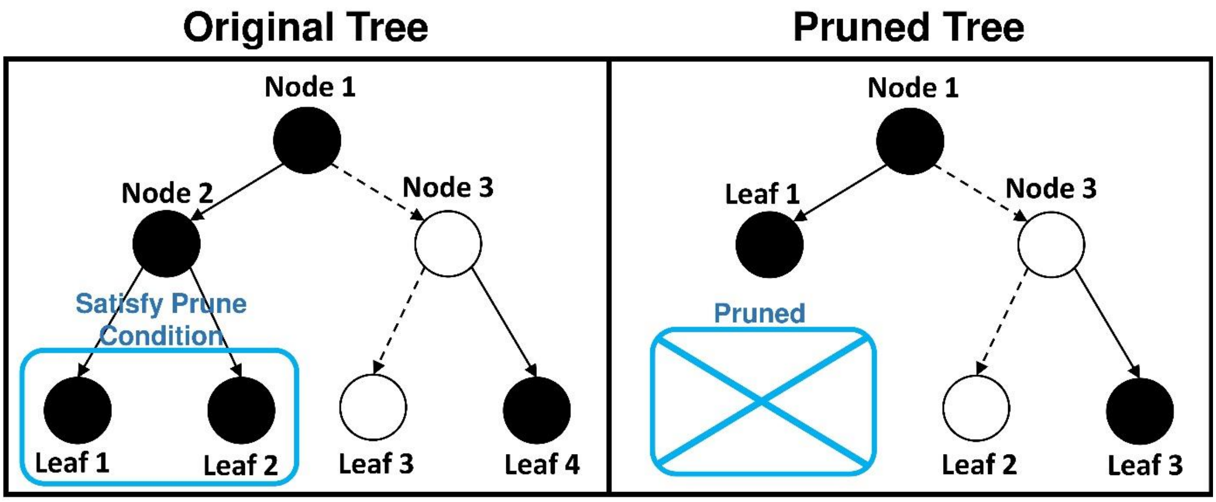


Figure 6: *Visual decision tree pruning illustration*

The hyper-parameters for training the decision tree classifier are the maximum depth of the tree (Max Depth), minimum samples to activate further splitting (Min Sample Split), the minimum weight fraction of leaf node samples with respect to input samples (Min Weight Fraction) and minimum impurity decrease. We have carefully selected logical limits of the hyper-parameter optimization problem by trial and error to provide faster convergence of the optimization algorithm. The limits for hyper-parameter optimization can be found in Table 4:

Table 4: *Limits for hyper-parameters in the decision tree*

Hyper-parameters	Minimum Limit	Maximum Limit
Max Depth	3	50
Min Sample Split	10	40
Min Weight Fraction	0	0.001
Min Impurity Decrease	0	0.001

Gaussian process Bayesian optimization was used for the hyper-parameter optimization. The kernel that was used is the Matern kernel with v =5/2 and small α_0 (1e-6) was according to Eq. (27):

$$C_v(d) = \sum_0 (x, x') = \alpha_0 \frac{2^{1-v}}{\Gamma(v)} \left(\sqrt{2v}\, \|x - x'\|\right)^v K_v \left(\sqrt{2v}\, \|x - x'\|\right) \tag{27}$$

Where K_v is the modified Bessel function and Γ is the gamma function. The kernel serves as the prior of the function of tree accuracy with respect to hyper-parameters. The posterior distribution of the function is then estimated using all available data, and the maximal point is estimated and measured. This process repeats iteratively until convergence.

2.5.2 "Rules-based" datasets

The "rules-based" datasets consists of three scenarios with different sets of generated data. The "Base case 2" acts as a reference scenario for the "rules-based" datasets. The "No ASS sale" scenario examines the impact of the marketability of an ammonium sulphate solution. The "CHP bonus" scenario analysis the effect of bonuses for CHP production (Chapter 2.4.2).

In contrast with decision analysis (Chapter 2.5.1), the MC simulation mode used for generation of "rules-based" datasets requires data which reflects the real operational conditions. For this case, simply including unrealistic combinations would lead to biased results. That is why some rules towards realistic combinations were introduced. The objective of these rules is to modify the probability distribution or the functional dependency of the variables so that it gives a better representation of the real situation. However, there is still some fluctuation along this dependency determined by the uniform distribution. The rules are described in more detail below and are visualized in Figure 7. Variables which are strictly independent are generated from the same uniform distribution used in the case of the decision analysis.

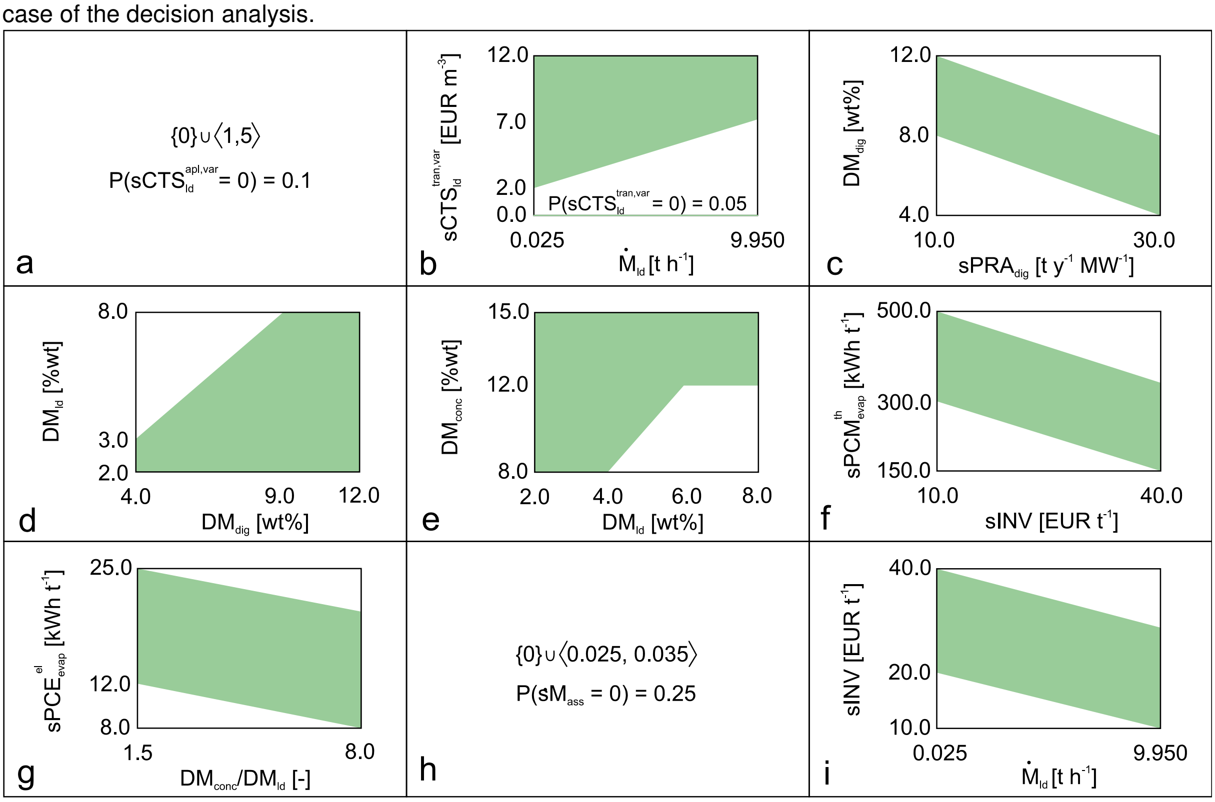


Figure 7: *Matrix for Monte Carlo simulation limits of the "rules-based" scenarios, h) is not valid for the "No ASS sale" scenario*

The first of the rules considers the fact that in some cases, the application costs may be zero. In these cases, known to us from the Czech Republic, the fertilizer is collected by local farms free of charge. We estimate the chance for zero application costs 10 % (Figure 7a). Otherwise, this cost is between 1 and 5 EUR/m^3.

Certain BGPs do not have any costs related to LD transport outside the plant itself. This situation is typical when there is some kind of barter exchange between closely located farmers (who provide biomass substrate for free or with discount) and BGP, which processes the biomass and provides a valuable natural fertilizer. Such a BGP may not have any agricultural production at all, hence the cost-free collection of LD by local farmers is highly appreciated. We suppose 5 % of BGPs to fulfil this scenario ($sCTS_{ld}^{apl,var}$= 0 EUR/m^3). If the transport cost is non-zero another rule is applied. Since BGPs with high installed capacity (high LD production) need a larger area of land for discharge LD, we may expect that also their average transport distance will be higher. Hence we set a rule for all "rules-based" scenarios, which generates higher $sCTS_{ld}^{tran,var}$for high capacity BGPs (Figure 7b). For instance, if $\dot{M}_{ld}$ = 0.025 t/h the value of $sCTS_{ld}^{tran,var}$ can be generated from the range between 2 and 12 EUR/m^3. If $\dot{M}_{ld}$ = 9.95 t/h the value of $sCTS_{ld}^{tran,var}$ can be generated from the range between 7 and 12 EUR/m^3.

A rule of high DM_{dig} – low $sPRA_{dig}$ and low DM_{dig} – high $sPRA_{dig}$ was applied (Figure 7c) since high water content results in high volumes of digestate (Drosg et al., 2015). DM in LD (DM_{ld}) is estimated to be between 2 and 8 % with respect to Møller et al. (2002), Drosg et al. (2015) and own experience and is restricted to be always less than DM_{dig} according to Figure 7d.

ES should provide reasonably higher DM content in a concentrate compared to LD. To guarantee reasonable difference between DM_{conc} and DM_{ld} the rule depicted in Figure 7e is introduced so the difference lesser than 4 % is impossible.

With the increase in thermal efficiency of the ES ($sPCM_{evap}^{th}$), we can expect high specific investment costs ($sINV$) as a result of more intensive heat recovery and increased requirements for heat transfer area. This rule for "rule-based" scenarios is applied according to Figure 7f.

Since the $sPCE_{evap}^{el}$ is often declining with the increase of volume reduction (Vondra et al., 2018a), i.e. with high freshwater production, a restriction is acquired as a part of the "rules-based" scenarios (Figure 7g).

For the "No ASS sale" scenario we assume that no ASS is sold. In this way, we demonstrate the influence of N recovery and marketability on the project feasibility. For the remaining scenarios, we still assume 25% probability that no ASS is sold (i.e. $s\dot{M}_{ass}$ = 0). However, if ASS is successfully sold its value is between 0.025 and 0.035 EUR/t (Figure 7h).

Since high capacity projects are generally favourable for specific investment costs, we assume for the "rules-based" scenarios that $sINV$ will decrease with the mass flow rate of LD (Figure 7i).

The CHP bonus can be used to support BGP operation and motivate operators to usefully utilize waste heat at the same time. It is up to authorities what is considered as useful utilization. In this study, it is assumed that ES represents useful utilization. There may be many strategies for the CHP bonus application. For instance, only the amount of the net electricity production corresponding to the usefully utilized heat is subsidized. Or, if more than 50 % of the heat is usefully utilized the whole net electricity production is subsidized, etc. It is not possible to consider all possible strategies in the model.

Therefore, in order to simplify it, the whole net electricity production is subsidized in the "CHP bonus" scenario. However, the value of the CHP bonus is influenced by the feed-in-tariff and the heat utilization prior to ES integration. It is assumed that the higher the feed-in-tariff the lower the CHP bonus because high support by a government is already provided by high feed-in-tariff. Further, it is assumed that the higher heat utilization the lower the CHP bonus because those operators who currently utilize high amount of heat already have (probably) CHP bonus virtually included in the feed-in-tariff. The model for CHP bonus is depicted in Figure 8. It is assumed that BGP with the current heat consumption higher than 80 % of the total production already has the CHP bonus included in the feed-in-tariff even when its value is only 0.06 EUR/kWh. On the other hand, if BGP has the heat utilization lower than 40 % of the total production and the feed-in-tariff lesser than 0.2025 it gets the CHP bonus and its value depends on the precise value of the feed-in-tariff. The highest CHP bonus of 0.05 EUR/kWh was inspired by the support scheme in Finland (European Commission, 2019b). In this study, the CHP bonus could be claimed only in the "CHP bonus" scenario.

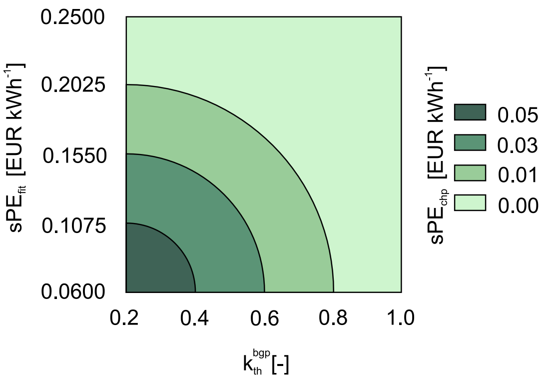
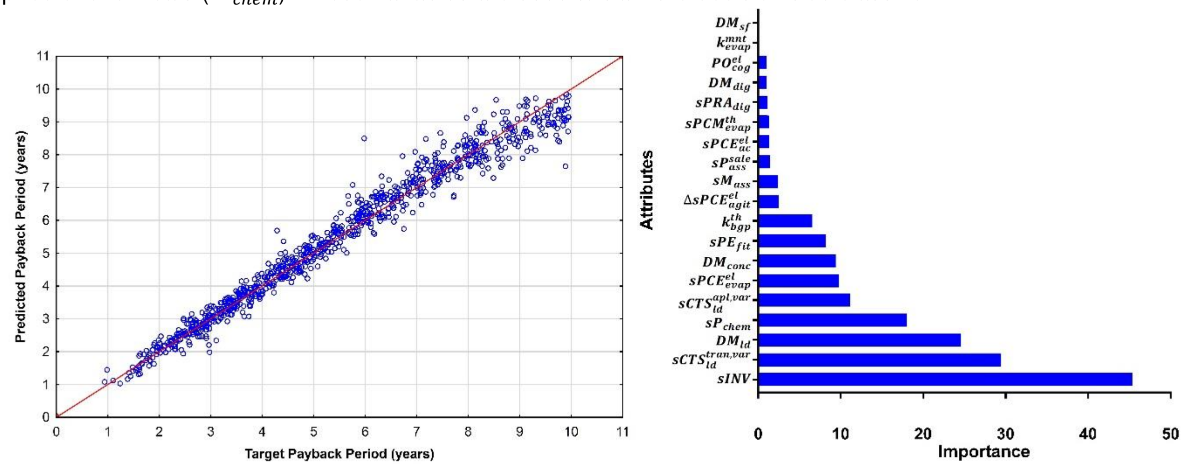


Figure 8: *Monte Carlo simulation limit for the CHP bonus variable*

3. Results and discussion

3.1 Base case 1 (“no rules-based" dataset)

Using the dataset from the Monte Carlo simulation, a neural network was trained to predict the payback period of the implementation of evaporation systems given the conditions and criteria. The automated neural network architectural search found a configuration of MLP 17-10-1 (exp-exp), where variables with insignificant variance were automatically ignored. The simple artificial neural network validated with 0.996 accuracy (see Figure 9a) while showing the importance value of each variable by sensitivity analysis (see Figure 9b). There are two “knee points” within the importance plots, one being after the 4th variable (from bottom) and another after the 9th variable. The drastic change of gradients in these “knee points” signifies that those are the threshold for variable screening. In this work, we choose the first 4 variables instead of 9 variables considering the complexity and user experience for the decision maker. The four most significant variables are the specific investment cost per LD ($sINV$), the specific cost for concentrated LD transport ($sCTS_{ld}^{tran,var}$), DM concentration in LD (DM_{ld}), and the specific price of chemicals (sP_{chem}). These variables are used to train the decision tree classifier.



(a) *(b)*

Figure 9: (a) *Neural network expected validation result against actual result* ***(b)*** *Importance of variables in scree plot*

Hyper-parameter optimization was implemented for training the decision tree classifier to achieve high validation accuracy. Using Bayesian optimization, the maximum validation error was found in 5 iterations. The algorithm was further iterated for 25 steps and the validation error remains unchanged (Figure 10). This shows that the tree generated has at least an epsilon-optimal hyper-parameter setting to achieve high validation performance. The tree was able to achieve 98.14% of validation error in a stochastic environment.

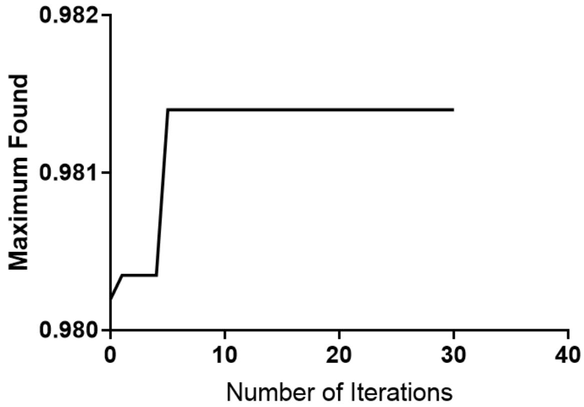


Figure 10: *Maximum validation accuracy and number of iterations by Bayesian optimization*

The full decision tree diagram can be found in the Appendix A. Statistically, there is more than 95% chance of getting infeasible economics by evaluating the full decision space and their outcomes when implementing the ES. This reflects that the economics for treating digestate in the European Union is particularly difficult and generally unfavourable as of now. Successful biogas projects require significant effort from both policy and management (Gebrezgabher et al., 2010). Searching for a good heuristic for stakeholders to implement such evaporation system is absurdly difficult and can be described as “searching for a needle in a haystack”. The main management effort of such project is to market the recovered ASS, while CHP incentives are provided by governments (European Commission, 2018) to encourage such efforts. The effect of these important but inadequate efforts will be comprehensively analysed in Section 3.2. Nevertheless, by screening through variables with the decision tree, we can essentially improve this situation to benefit the decision maker. This is computed by the decision tree classifier to separate the full decision space into subspace that are representative of fast PP (0-3 years), average PP (3-5 years) and infeasible implementation. The decision tree classifier can elegantly classify such datasets by only using sequence of univariate inequality constraints (see Table 4). The simplicity of using such univariable inequality constraints as a heuristic for decision making is highly effective and convenient for stakeholders. Selecting two of the highest probability pathways for fastest payback (0-3 years), a branch of the tree diagram is generated and shown in Figure 11.

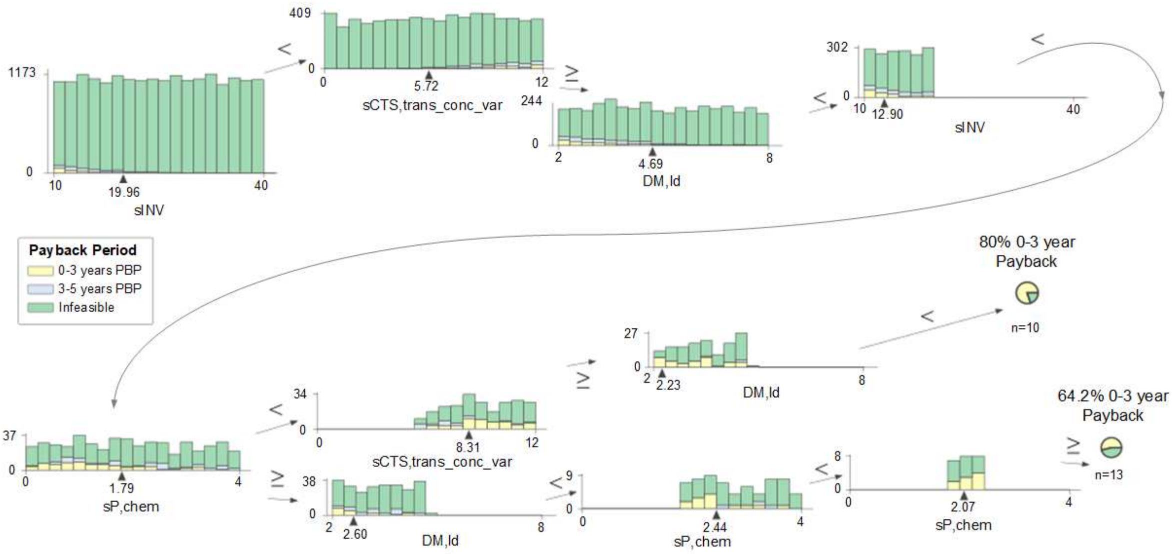


Figure 11: Branch of decision tree that indicates interesting pathways for fast payback period

An interesting pathway that was generated is shown in Figure 11. The tree suggests that there is a compelling opportunity of between 0-3 years payback with 80% probability. This can be achieved by having specific investment costs per LD below 12.90 EUR/t, DM concentration in LD below 2.23 wt%, specific cost for LD transport and specific price of chemicals over 8.31 EUR/m^3 and below 1.79 EUR/t respectively.

An alternative pathway can also be identified in Figure 11, where there is a 64.2% probability of achieving 0-3 years payback. This can be achieved by having similar a specific investment costs as the previous pathway, maintaining the specific price of chemicals between 2.07-2.44 EUR/t while having specific cost for LD transportation and DM concentration in LD below 5.72 EUR/m^3 and 2.6 wt% respectively. Although there is a range for the specific price of chemicals, decision makers should only consider the upper limit, as lower chemical prices give better economic feasibility. Technically, the lower boundary of sP_{chem} gives confinement of the subspace so that the probability of success can be qualitatively assessed. The criteria for each evaporation implementation decision pathway is tabulated in Table 5 for a visualized comparison.

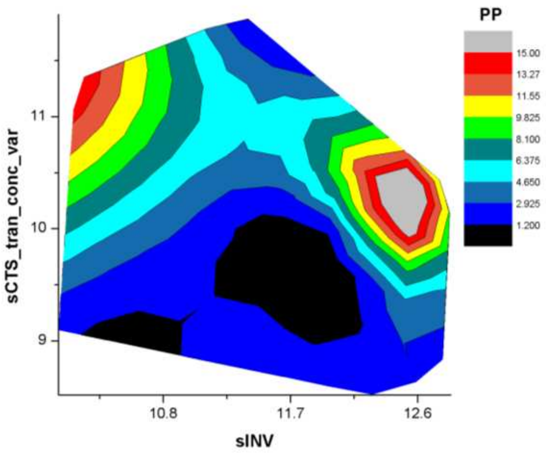
Table 5: *Criteria and reward for pathways*

Solutions	Pathway 1	Pathway 2
Criteria	Specific investment cost per tonne of liquid digestate (EUR/t) <12.90	Specific investment cost per tonne of liquid digestate (EUR/t) <12.90
	Specific cost for liquid digestate transport (EUR/m^3) >8.31	Specific cost for liquid digestate transport (EUR/m^3>5.72
	Dry matter concentration in liquid digestate (wt%) < 2.23	Dry matter concentration in liquid digestate (wt%) < 2.6
	Specific price of chemicals (EUR/t) <1.79	2.07< Specific price of chemicals (EUR/t) <2.44
Payback	0-3 years payback with 80% probability	0-3 years payback with 64.2%

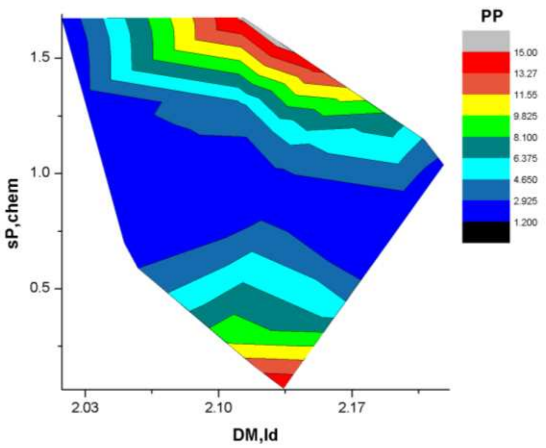
To achieve short PP within an ES implementation project, specific investment cost must be generally lower than a threshold of 12.90 EUR/t. Having a higher specific cost for concentrated LD transport improves the stability of the project as the probability of success improves. The implementation of ES is also more economically favourable for low DM content of LD and specific price of chemicals below 1.79 and 2.44 EUR/t respectively. Low DM content (< 2.23%, <2.6% respectively) could be achieved by acquiring mechanical separator with high separation efficiency (decanter centrifuge, screw press with fine sieve). The specific price for chemicals depends on the amount of ammonia that must be removed during the thickening process. Avoiding a nitrogen-rich substrates (e.g. poultry manure, grass silage) and requiring efficient management of chemical dosage in ES could be considered as beneficial steps for achieving short PP.

Using transportation distance estimation from Ghafoori et al. (2007), we estimate that the minimum truck transport distance for pathway 1 is 31.94 km and pathway 2 is 18.7 km. These minimum transportation distance acts as a reference for decision makers if the specific cost for LD transport is unknown. Vilanova Plana and Noche (2016) discussed that the mode of transportation and storage time also affects the specific transportation costs, and it is recommended that such considerations are made by decision makers.

A probabilistic result was presented in the decision tree, we perform further analysis on the best pathway (Pathway 1) to show the nature and causes of success and failure within the class. In order to study the micro-behaviour of variables within the class of the pathway, the respective solution space has been plotted as contour plots in Figure 12.



(a)



(b)

Figure 12: *Solution space of pathway 1 considering (a) specific transportation costs of LD and specific investment costs per tonne of LD (b) specific price of chemicals and DM concentration in LD*

The solution space for Pathway 1 is plotted in Figure 12, there is an obvious multi-dimensional saddle. The decision tree has successfully found a solution space where there is a stable multi-dimensional local minima. This saddle can be found in Figure 12a (where there is a light blue gap) and Figure 12b (where there is a dark blue gap). For both plots, the contours are smooth and move towards high PP towards the edges of the solution space. This shows that making decisions that are bounded within this solution space has a smooth and resilient outcome and do not cause sudden infeasibility due to dynamic changes. This attribute of the pathway is critically important for real-world implementation, as it gives allowance for slight error during actual project implementation. Pathway 2, on the other hand, only has a 64.2% of having a fast PP (see Table 5) which is not robust. Although Pathway 2 can potentially be a "high-risk high-reward" decision option, we highly recommend making decisions that follow Pathway 1 as it is much more stable (as presented by the solution space contour plots).

3.2 "Rules-based" datasets

Figure 13 shows the distribution of PP for all "rules-based" scenarios. Note that only PP from 0 to 15 years is assumed to be feasible. They represent approx. 2.7% and 6.7% of all samples generated in "Base case 2" and "CHP bonus" scenarios respectively. Long PP, negative cash flow or lack of available heat for evaporation are denoted as infeasible. Obviously, there is a dramatic increase of feasible scenarios in case of "CHP bonus". This is valid for short PP (< 5 years) in particular. Clearly, CHP bonus introduction significantly supports a digestate integration into BGP. In comparison with the "Base case 2" scenario, there is an increase of feasible samples by 251%. Missing market with ASS ("No ASS sale" scenario) does not influence PP significantly. There is a decrease of feasible simulations by 16% against the "Base case 2". This result suggests that ASS marketing is not necessarily a decisive factor for the LD processing project. To be more impactful, the LD treatment must be capable of producing more valuable products or exploit more fertilizer or otherwise marketable substances.

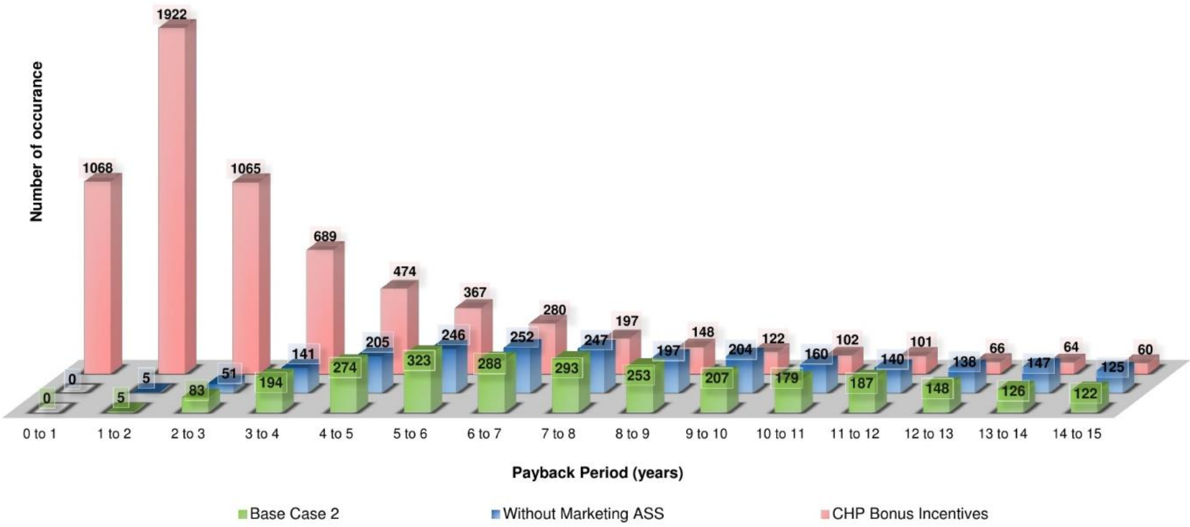


Figure 13: Overall difference in payback period occurrence with different scenarios

In the following part, the distribution of individual independent variables is discussed together with the impact of each scenario. The histograms are shown for PP from 0 to 5 years as it is the most attractive range for decision makers. Moreover, the same range was used for classification in the decision tree design.

Specific transport costs ($sCTS_{ld}^{tran,var}$) is one of the most important variables. CHP bonus decreases its importance (Figure 14); however, it remains quite big - 26 % of feasible samples has a value higher than 11 EUR/m^3. For "Base case 2" and "No ASS sale", the values higher than 11 EUR/m^3 are dominant with more than 60 % of feasible samples. Clearly, without CHP bonus, the LD processing is valuable mainly in regions where high transportation cost due to longer distances is expected, e.g. regions with high density of agriculture production, with a high geographical density of BGPs or regions with legal restrictions.

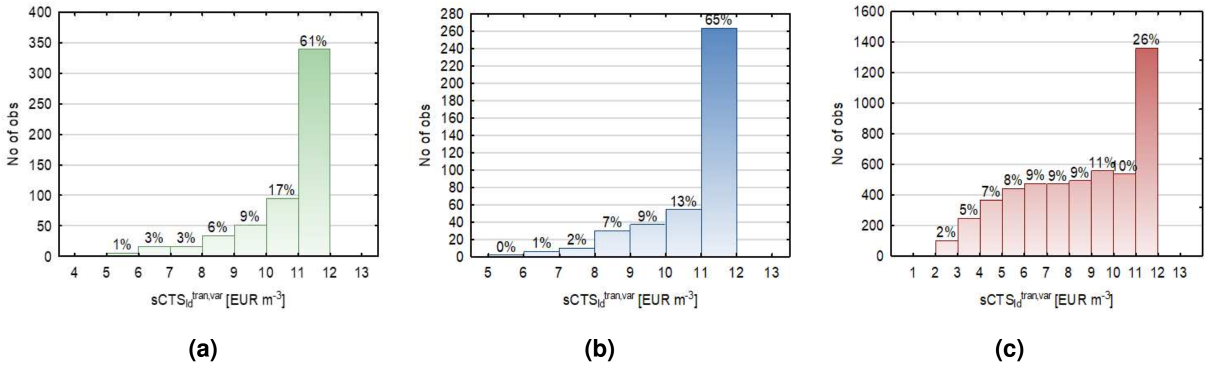


Figure 14: Distribution of specific LD transportation price in the successful scenario of (a) „Base case 2“ (b) „No ASS sale“ (c) „CHP bonus“ incentives

Another variable with interesting results is the installed power output of a BGP (PO_{cog}^{el}), which basically describes its capacity. BGP with higher installed electricity output have also high digestate production and therefore lower $sINV$ (see rules – Figure 7). At the same time, it is likely that transport cost is higher because the amount of LD is higher and has to be transported between longer distances. Since the average installed capacity in EU is around 0.56 MW (Deremince and Königsberger, 2017), the simulated results (Figure 15) has shown that there is approx. a 3 times lower chance of a successful implementation of evaporation system into the current industrial settings in comparison with BGPs with installed capacity higher than 2.5 MW. On the other hand, it is obvious that due to economies of scale BGP with high capacities (> 1.0 MW) have higher chance of successful implementation - only 20% of BGPs under 1 MW were able to succeed within the feasible samples in the "Base case 2". Thus the LD thickening project in an average BGP in the EU will probably be hardly feasible. Centralization of digestate treatment for small (< 1.0 MW) neighbouring BGPs could be advantageous in this regard. Nevertheless, referring Figure 15c, the aforementioned difficult project implementation can be improved with increased CHP bonus which allows smaller capacity BGP to be more successful.

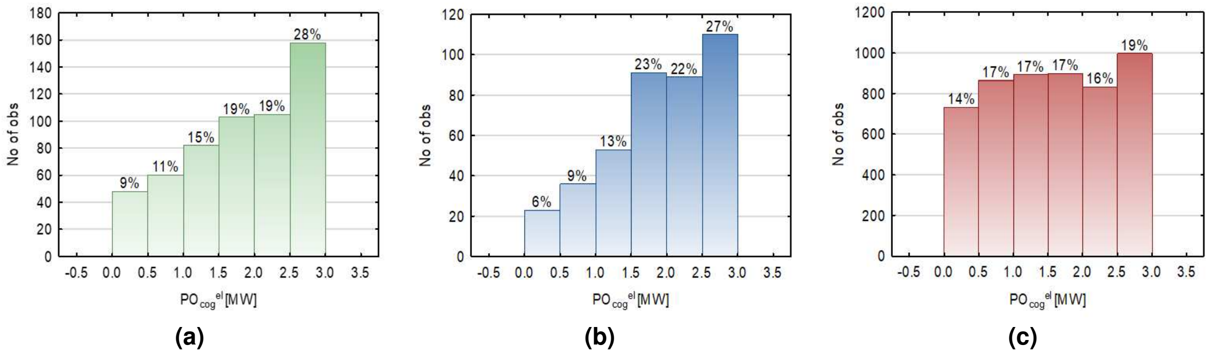
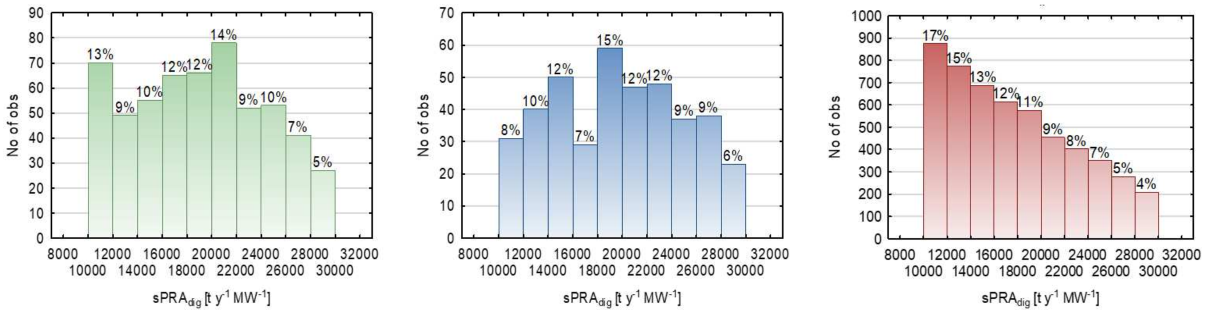


Figure 15: Distribution of installed electric power output in the successful scenario of (a) „Base case 2“ (b) „No ASS sale“ (c) „CHP bonus“ incentives

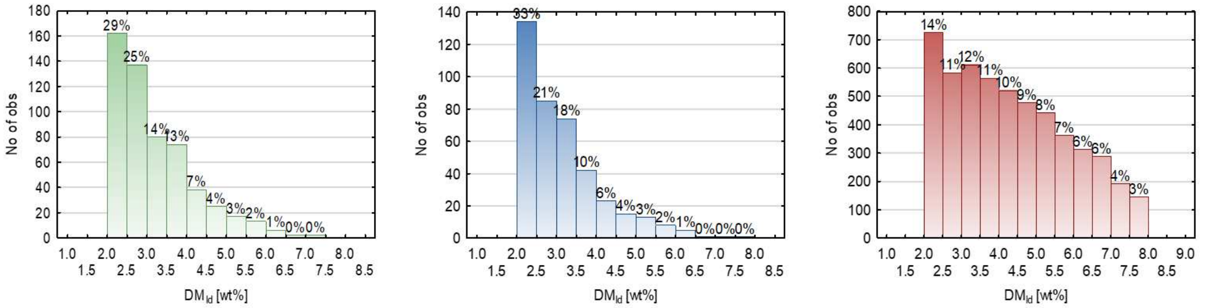
Furthermore, the distribution of the values of $sPRA_{dig}$ was investigated (see Figure 16). Once again, the effect of increased CHP incentives has a large impact on the distribution. The explanation is as follows, the higher $sPRA_{dig}$ the lower $DM_{dig}$and therefore more water need to be evaporated. This results in heat demand increase. The samples with high $sPRA_{dig}$ (especially those with > 20 000 t $^{y-1}$ MW^{-1}) can easily become infeasible due to lack of available heat compared to the samples with low $sPRA_{dig}$. Evidently, we identify that the number of observations is decreasing with increasing $sPRA_{dig}$. This nature is not observable in case of "Base case 2" and "No ASS sale" scenarios. The reason is that CHP bonus makes feasible even those BGPs with low potential of LD volume reduction (high DM_{dig}). So, BGPs with low $sPRA_{dig}$ (high DM_{dig}) are more prone to be infeasible in case of "Base case 2" and "No ASS sale" while they are more feasible in case of "CHP bonus".



(a) (b) (c)

Figure 16: Distribution of specific production of digestate in the successful scenario of (a) „Base case 2" (b) „No ASS sale" (c) „CHP bonus" incentives

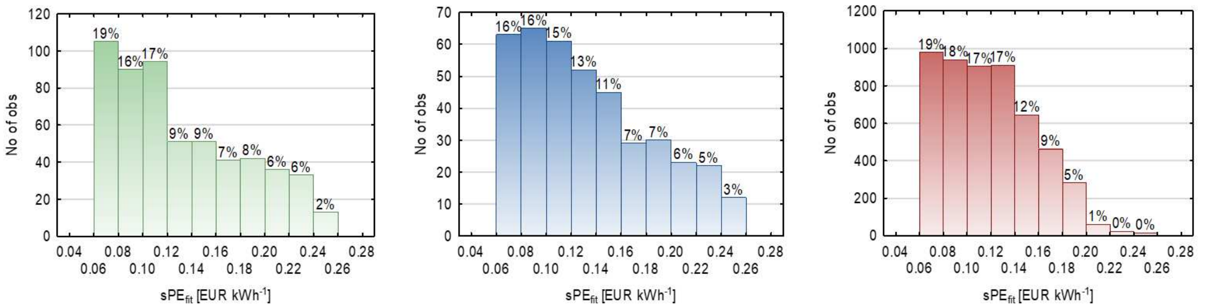
Figure 17 shows the distribution of DM_{ld}. Obviously, more efficient mechanical separation (less DM in LD) significantly increases the probability towards a feasible solution. Nearly 90 % of feasible samples has DM_{ld} up to 4.5 wt%. CHP bonus decreases the significance of this variable, but it remains important. Low DM_{ld} enables significant volume reduction in the ES thus contributes to high savings in transport and spreading. For BGPs with high DM content (> 4.5 wt%) in LD it could be beneficial to accordingly adjust the operation of their mechanical separator, e.g. using a finer screen or increasing the resistance force in case of screw press separator.



(a) (b) (c)

Figure 17: Distribution of DM concentration in LD in successful scenario of (a) „Base case 2" (b) „No ASS sale" (c) „CHP bonus" incentives

Electricity feed-in tariffs (sPE_{fit}) play an important role in terms of return on investment. In the "Base case 2" and "No ASS sale" scenarios around 50% of successful samples lie below the value of 0.12 EUR/kWh (Figure 18). This suggests that high incentives for electricity production do not promote projects on LD treatment as the power consumption of newly acquired technologies is too costly for BGP operators. Since high feed-in tariffs (> 0.1075 EUR/kWh) are penalized in the "CHP bonus" scenario (see Figure 8), the feasibility of samples with low value of sPE_{fit} is even more prevalent in this scenario (Figure 18c).



(a) (b) (c)

Figure 18: Distribution of specific price for electricity (feed-in tariffs) in successful scenario of (a) „Base case 2" (b) "No ASS sale" (c) „CHP bonus" incentives

The other variables' histograms can be found in the Appendix B, but their distributions are briefly commented in the following part. Majority of the feasible samples (about 90 %) has $sCTS_{ld}^{apl,var}$ higher than 2 EUR/m^3 and, at the same time, the higher $sCTS_{ld}^{apl,var}$ the more feasible samples (Figure B.1). However, when CHP bonus is introduced, the distribution of the feasible samples becomes uniform. So, the importance of this variable is decreased by CHP. It is also the case of k_{evap}^{mnt} (Figure B.2). The only difference is that the higher value (up to 0.15) the lesser feasible samples. sP_{chem} (Figure B.3) is very similar to k_{evap}^{mnt} following the trend the higher value (up to 4 EUR/t) the lesser feasible samples. All these variables have one feature in common – CHP bonus significantly decreases their impact.

On the other hand, the following discussion of results includes the variables with small sensitivity to the introduction of CHP bonus. DM_{dig} (Figure B.4) seems to be normally distributed along the most frequent value, which is 8 wt%, so no impact is observed. This is also valid for $sPCM_{evap}^{th}$ (Figure B.5) where the most frequent value is about 300 kWh/t. In any case, the availability of a sufficient amount of heat with regard to LD production and ES thermal efficiency is a prerequisite for the success of the project. As far as DM_{conc} is concerned, it follows the rule the higher content (up to 15 wt%) the more feasible samples (Figure B.6). DM_{sf} (Figure B.7) has rather uniform distribution within the range from 20 to 35 wt% and its importance is negligible. In the case of k_{bgp}^{th} (Figure B.8), it holds that the higher value (up to 1) the lesser feasible samples. This is an expected result as the lack of available heat makes a sample infeasible. $sPCE_{ac}^{el}$ has an almost uniform distribution and negligible effect (Figure B.9). $\Delta sPCE_{agit}^{el}$ has the same nature (Figure B.10). $s\dot{M}_{ass}$ (Figure B.11) distribution is influenced by the "No ASS sale" scenario. Naturally, there are more feasible samples when $s\dot{M}_{ass}$ is higher (up to 0.035 wt%) because the product can be sold. It is distributed in the opposite way for the other two scenarios. sP_{ass}^{sale} (Figure B.12) is only relevant for "Base case 2" and "CHP bonus" scenarios and is almost uniformly distributed with small effect. Specific investment cost $sINV$ (Figure B.13) is normally distributed among the most frequent value of 25 EUR t-1 in the "CHP bonus" scenario. However, it is slightly biased towards lower values (down to 10 EUR/t). In the "Base case 2" and "No ASS sale" scenarios, around 93% and 97% of successful samples respectively lie below the value of 30 EUR per tonne, which makes this value a significant threshold.

4. Conclusion

Advancement in digestate treatment systems is the next step towards creating a circular economy. This paper recommends the utilization of vacuum evaporator systems as they are robust and effective. Nevertheless, the decision in implementing evaporator systems within existing biogas facilities and infrastructure is non-straightforward. Stakeholders are required to make decisions considering multiple dimensions of varying factors that will affect the plant economics. A novel techno-economic analysis tool was developed for assessing scenarios of the economic feasibility of such retrofitting of evaporator systems. Monte Carlo simulations resulted in a high percentage of infeasible solutions (more than 95% probability), which suggests that project feasibility is highly sensitive to operational parameters and BGPs have a low randomized probability of being economically justified when investing into the thickening technology. Performing critical variable selection on a trained artificial neural network, four of the most influential variables were identified as the specific investment cost per LD, specific cost for LD transport, DM concentration in LD and specific price of consumed chemicals. A novel decision tree was utilized to search for a sets of decision that would yield reliable and fast the payback period. Stakeholders can also conveniently utilize the decision tree as it provides decision-making heuristic in the form of sequential univariate inequality. Two feasible pathways were suggested by the decision tree to achieve a fast payback period (below 3 years). Analysing the solution space, one of the pathways gave a resilient and stable solution with 0-3 year payback period and probability of 80%, while the other pathway gave a "high-risk high-reward" solution with 0-3 year payback period and probability of 64.2%. These pathways can be easily achieved by planning the technical implementation and financial investment into such project carefully.

Statistical evaluation of the impact of each scenario for rules-based datasets was also investigated. It showed that only about 2.5% and 2% of samples are feasible with PP up to 5 years (the most attractive) for "Base case 2" and "No ASS sale" scenario. On the other hand, it is about 10% for "CHP bonus" scenario. Detailed analysis of the distribution of independent variables was also carried out. It revealed several main conclusions:

- high transport cost (> 8 EUR m^{-3}) is almost the necessary condition without CHP bonus,
- neighbouring small-scale BGPs should implement centralized treatment, which has lower specific investment/maintenance cost,
- even BGPs with low potential for reduction of LD volume (DM concentration in LD > 4.5 wt%) have short PP when CHP bonus is introduced; generally, the introduction of CHP bonus has a strongly positive effect (increase of feasible projects by 251%);
- efficient mechanical separation (DM concentration in LD < 4.5 wt%) has a very positive impact on PP,
- high feed-in tariffs (> 0.12 EUR/kWh) have a negative impact on the project's feasibility,
- ASS production and sale have slightly positive effect on PP, but in most cases not the decisive effect.

The results of this work are published in hopes to aid the decision making for the implementation of evaporation systems, thus reducing untreated LD residues within the biogas industry. The future work will be focused on extending the model by the process of anaerobic digestion and including more aspects related to the specific composition of the digestate. Also, a more detailed calculation of other separation processes will be implemented.

Nomenclature

CTS	Costs, EUR	$agit$	Agitators in storage tanks
DM	Dry matter content, wt%	apl	Field application
INV	Investment costs, EUR	ass	Ammonium Sulphate solution
k	Coefficient, -	bgp	Biogas plant
$\dot{M}$	Mass flow rate, kg h^{-1}	$chem$	Chemicals
PC	Power consumption, kW	chp	Combined heat and power
PO	Power output, MW	$conc$	Concentrate
PP	Payback period, y	cog	Cogeneration unit
REV	Revenues, EUR	dig	Digestate
SH	Service hours, h y^{-1}	el	Electric power
$sCTS$	Specific costs, EUR m^{-3}	$evap$	Evaporation technology
$sINV$	Specific investment costs, EUR t^{-1}	fit	Feed-in tariff
$s\dot{M}$	Specific mass flow rate, wt%	fw	Fresh water
sP	Specific price, EUR t^{-1}	ld	Liquid digestate
$sPCE$	Specific power consumption, kW MW^{-1}	mnt	Technology maintenance
$sPCM$	Specific power consumption, kWh t^{-1}	new	New scenario (with $evap$)
sPE	Specific price of electricity, EUR kWh^{-1}	$orig$	Original scenario (without $evap$)
$sPRA$	Specific production annual, t y^{-1} MW^{-1}	$sale$	Sale of product
$\dot{V}$	Volumetric flow rate, m^3 h^{-1}	sf	Solid fraction
η	Efficiency, -	$strg$	Storage
ρ	Density, kg m^{-3}	th	Thermal power
Indices		$tran$	Transportation
ac	Air-cooled chillers	var	Variable (costs)

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References

Al Seadi, T., Drosg, B., Fuchs, W., Rutz, D., Janssen, R., 2013. Biogas digestate quality and utilization, in: The Biogas Handbook. Elsevier, pp. 267–301. doi.org/10.1533/9780857097415.2.267

Auburger, S., Wustholz, R., Petig, E., Bahrs, E., 2015. Biogas digestate and its economic impact on farms and biogas plants according to the upper limit for nitrogen spreading—the case of nutrient-burdened areas in north-west Germany. AIMS Energy 3, 740–759. doi.org/10.3934/energy.2015.4.740

Azouma, Y.O., Jegla, Z., Reppich, M., Turek, V., Weiß, M., 2018. Using agricultural waste for biogas production as a sustainable energy supply for developing countries. Chem. Eng. Trans. 70, 445–450. doi.org/10.3303/CET1870075

Bamelis, L., Blancke, M.A., Camargo-Valero, L., De Clercq, A., Haumont, B., De Keulenaere, F., Delvigne, E., 2015. Techniques for nutrient recovery from digestate derivatives. www.biorefine.eu/sites/default/files/publication-uploads/wp2a5_gxabt_20151216_recovery_techniques_-_digestate.pdf (accessed 7 May 2019).

Berglund, M., Börjesson, P., 2006. Assessment of energy performance in the life-cycle of biogas production. Biomass Bioenergy 30, 254–266. doi.org/10.1016/j.biombioe.2005.11.011

Bolzonella, D., Fatone, F., Gottardo, M. and Frison, N., 2018. Nutrients recovery from anaerobic digestate of agro-waste: Techno-economic assessment of full scale applications. J Environ Manage, 216, pp.111-119. doi: 10.1016/j.jenvman.2017.08.026

CDPQ Decision Tools, 2018. Centre de developpement du porc du Quedec inc. //www.cdpq.ca/outils-d-aide-a-la-decision.aspx (accessed 9 May 2019)

Chen, Y.C., Yang, Z.M., Chen, Q.H., Jiang, X.L., Gao, M. and Xia, Q., 2009. An overview on disposal of anaerobic digestate for large scale biogas engineering. China biogas, *28*(1), pp.14-20.

Chiumenti, A., da Borso, F., Chiumenti, R., Teri, F., Segantin, P., 2013. Treatment of digestate from a co-digestion biogas plant by means of vacuum evaporation: Tests for process optimization and environmental sustainability. Waste Manag. 33, 1339–1344. doi.org/10.1016/j.wasman.2013.02.023

Cordes, F., 2018. Vacuum evaporation as system provider for flexible biogas plants, in: Progress in the Treatment and Application of Manure and Digestate Products. Presented at the Progress Manure and Digestate 2018, German Biogas and Bioenergy Society (GERBIO), Schwäbisch Hall, Germany.

CZBA - Czech Biogas Association, 2014. Strategická výzkumná agenda oboru bioplyn. www.czba.cz/files/ceska-bioplynova-asociace/uploads/files/SVA_CzBA_2014_FINAL.pdf (accessed 7 May 2019).

Dahlin, J., Herbes, C. and Nelles, M., 2015. Biogas digestate marketing: Qualitative insights into the supply side. Resour Conserv Recycl, *104*, pp.152-161. doi: 10.1016/j.resconrec.2015.08.013

Daniel-Gromke, J., Rensberg, N., Denysenko, V., Trommler, M., Reinholz, T., Völler, K., Beil, M., Beyrich, W., 2017. Anlagenbestand Biogas und Biomethan – Biogaserzeugung und nutzung in Deutschland. DBFZ Deutsches Biomasseforschungszentrum gemeinnützige GmbH, Leipzig.

Dasa, K.T., Westman, S.Y., Millati, R., Cahyanto, M.N., Taherzadeh, M.J., Niklasson, C., 2016. Inhibitory Effect of Long-Chain Fatty Acids on Biogas Production and the Protective Effect of Membrane Bioreactor. BioMed Res. Int. 2016, 1–9. doi.org/10.1155/2016/7263974

Deremince, B., Königsberger, S., 2017. Statistical Report of the European Biogas Association 2017. Brussels, Belgium. european-biogas.eu/wp-content/uploads/2017/12/Statistical-report-of-the-European-Biogas-Association_excerpt-web.pdf (accessed 14 December 2018).

Drosg, B., Fuchs, W., Al Seadi, T., Madsen, M., Linke, B., 2015. Nutrient Recovery by Biogas Digestate Processing. IEA Bioenergy.

Đurđević, D., Blecich, P., Lenić, K., 2018. Energy Potential of Digestate Produced by Anaerobic Digestion in Biogas Power Plants: The Case Study of Croatia. Environ. Eng. Sci. 35, 1286–1293. doi.org/10.1089/ees.2018.0123

European Commission, 2018. Energy - Cogeneration of heat and power. ec.europa.eu/energy/en/topics/energy-efficiency/cogeneration-heat-and-power (accessed 21 January 2019).

European Commission, 2019a. Horizon 2020, Work Programme 2018-2020. ec.europa.eu/programmes/horizon2020/en/what-work-programme (accessed 10 May 2019).

European Commission, 2019b. Renewable energy policy database and support. www.res-legal.eu/search-by-country/finland/single/ (accessed 21 January 2019).

Fagerström, A., Seadi, T.A., Rasi, S., Briseid, T., 2018. The role of Anaerobic Digestion and Biogas in the Circular Economy. IEA Bioenergy Task 37 2018 8.

Frischmann, P., 2012. Enhancement and treatment of digestates from anaerobic digestion (Desk top study on digestate enchancement and treatment). WRAP. www.wrap.org.uk/content/enhancement-and-treatment-digestates-anaerobic-digestion (accessed 10 May 2019).

Fuchs, W., Drosg, B., 2013. Assessment of the state of the art of technologies for the processing of digestate residue from anaerobic digesters. Water Sci. Technol. 67, 1984–1993. doi.org/10.2166/wst.2013.075

Gebrezgabher, S., Meuwissen, M., Prins, B. and Lansink, A., 2010. Economic analysis of anaerobic digestion—A case of Green power biogas plant in The Netherlands. NJAS - Wageningen Journal of Life Sciences, 57, 109-115.

Ghafoori, E., Flynn, P. and Feddes, J., 2007. Pipeline vs. truck transport of beef cattle manure. Biomass Bioenergy, 31, 168-175. doi: 10.1016/j.biombioe.2006.07.007

Golkowska, K., Vázquez-Rowe, I., Lebuf, V., Accoe, F. and Koster, D., 2014. Assessing the treatment costs and the fertilizing value of the output products in digestate treatment systems. Wat Sci Tech, 69(3), pp.656-662. doi: 10.2166/wst.2013.742

Gómez, X., Cuetos, M.J., Cara, J., Morán, A., García, A.I., 2006. Anaerobic co-digestion of primary sludge and the fruit and vegetable fraction of the municipal solid wastes. Renew. Energy 31, 2017–2024. doi.org/10.1016/j.renene.2005.09.029

Guercini, S., Castelli, G., Rumor, C., 2014. Vacuum evaporation treatment of digestate: full exploitation of cogeneration heat to process the whole digestate production. Wat Sci Tech 70, 479–485. doi.org/10.2166/wst.2014.247

Hung, C.Y., Tsai, W.T., Chen, J.W., Lin, Y.Q. and Chang, Y.M., 2017. Characterization of biochar prepared from biogas digestate. Waste Manage, 66, pp.53-60. doi: 10.1016/j.wasman.2017.04.034

Kirchherr, J., Reike, D., Hekkert, M., 2017. Conceptualizing the circular economy: An analysis of 114 definitions. Resour. Conserv. Recycl. 127, 221–232. doi.org/10.1016/j.resconrec.2017.09.005

Koszel, M. and Lorencowicz, E., 2015. Agricultural use of biogas digestate as a replacement fertilizers. Agric. Agric. Sci. Procedia, 7, pp.119-124. doi.org/10.1016/j.aaspro.2015.12.004

Liguori, R., Faraco, V., 2016. Biological processes for advancing lignocellulosic waste biorefinery by advocating circular economy. Bioresour. Technol. 215, 13–20. doi.org/10.1016/j.biortech.2016.04.054

Ma, H., Guo, Y., Qin, Y., Li, Y.-Y., 2018. Nutrient recovery technologies integrated with energy recovery by waste biomass anaerobic digestion. Bioresour. Technol. 269, 520–531. doi.org/10.1016/j.biortech.2018.08.114

Maier, C., 2018. Vapogant - digestate evaporator, in: Progress in the Treatment and Application of Manure and Digestate Products. Presented at the Progress Manure and Digestate 2018, German Biogas and Bioenergy Society (GERBIO), Schwäbisch Hall, Germany.

Máša, V., Bobák, P., Kuba, P., Stehlík, P., 2013. Analysis of energy efficient and environmentally friendly technologies in professional laundry service. Clean Techn Environ Policy 15, 445–457. doi.org/10.1007/s10098-013-0618-2

Melse, R.W., Verdoes, N., 2005. Evaluation of Four Farm-scale Systems for the Treatment of Liquid Pig Manure. Biosyst. Eng. 92, 47–57. doi.org/10.1016/j.biosystemseng.2005.05.004

Miltner, M., Makaruk, A., Harasek, M., 2013. Biomethane-Calculator, IEEE-project BioMethane Regions. bio.methan.at./?q=de/download_biomethane-calculator (accessed 10 May 2019).

Møller, H.B., Lund, I., Sommer, S.G., 2000. Solid–liquid separation of livestock slurry: efficiency and cost. Bioresour. Technol. 74, 223–229. doi.org/10.1016/S0960-8524(00)00016-X

Møller, H.B., Sommer, S.G., Ahring, B.K., 2002. Separation efficiency and particle size distribution in relation to manure type and storage conditions. Bioresour. Technol. 85, 189–196. doi.org/10.1016/S0960-8524(02)00047-0

Monfet, E., Aubry, G., Ramirez, A.A., 2018. Nutrient removal and recovery from digestate: a review of the technology. Biofuels 9, 247–262. doi.org/10.1080/17597269.2017.1336348

Monlau, F., Sambusiti, C., Ficara, E., Aboulkas, A., Barakat, A., Carrère, H., 2015. New opportunities for agricultural digestate valorization: current situation and perspectives. Energy Environ. Sci. 8, 2600–2621. doi.org/10.1039/C5EE01633A

Noel, V., Fourcroy, J., 2017. Eurovent rating standard for DX air coolers, air cooled condensers, dry coolers: RS 7/C/008 - 2017. Eurovent Certita Certification SAS. www.eurovent-certification.com/fic_bdd/en/1494596601_S02_D04_ECP-HE_2017_RS-7C008.pdf (accessed 18 December 2018)

Pablo-Romero, M. del P., Sánchez-Braza, A., Salvador-Ponce, J., Sánchez-Labrador, N., 2017. An overview of feed-in tariffs, premiums and tenders to promote electricity from biogas in the EU-28. Renewable Sustainable Energy Rev. 73, 1366–1379. doi.org/10.1016/j.rser.2017.01.132

Potting, J., Hekkert, M., Worrell, E., Hanemaaijer, A., 2017. Circular Economy: Measuring innovation in the product chain (Policy Report No. 2544). PBL Netherlands Environmental Assessment Agency. www.pbl.nl/sites/default/files/cms/publicaties/pbl-2016-circular-economy-measuring-innovation-in-product-chains-2544.pdf (accessed 10 May 2019).

Ragazzi, M., Maniscalco, M., Torretta, V., Ferronato, N., Rada, E.C., 2017. Anaerobic digestion as sustainable source of energy: A dynamic approach for improving the recovery of organic waste. Energy Procedia 119, 602–614. doi.org/10.1016/j.egypro.2017.07.086

Rehl, T., Müller, J., 2011. Life cycle assessment of biogas digestate processing technologies. Resour. Conserv. Recycl. 56, 92–104. doi.org/10.1016/j.resconrec.2011.08.007

Scarlat, N., Dallemand, J.-F., Fahl, F., 2018. Biogas: Developments and perspectives in Europe. Renew. Energy 129, 457–472. doi.org/10.1016/j.renene.2018.03.006

Tampio, E., Marttinen, S., Rintala, J., 2016. Liquid fertilizer products from anaerobic digestion of food waste: mass, nutrient and energy balance of four digestate liquid treatment systems. J. Clean. Prod. 125, 22–32. doi.org/10.1016/j.jclepro.2016.03.127

Uçkun Kiran, E., Stamatelatou, K., Antonopoulou, G., Lyberatos, G., 2016. Production of biogas via anaerobic digestion, in: Handbook of Biofuels Production. Elsevier, pp. 259–301. doi.org/10.1016/B978-0-08-100455-5.00010-2

van Haeff, J., 2015. The Role of Bio-waste in the Emerging Circular Economy. www.compostnetwork.info/wordpress/wp-content/uploads/John-van-Haeff.pdf (accessed 10 May 2019).

Vaneeckhaute, C., Lebuf, V., Michels, E., Belia, E., Vanrolleghem, P.A., Tack, F.M.G., Meers, E., 2017. Nutrient Recovery from Digestate: Systematic Technology Review and Product Classification. Waste Biomass Valorization 8, 21–40. doi.org/10.1007/s12649-016-9642-x

Venkata Mohan, S., Nikhil, G.N., Chiranjeevi, P., Nagendranatha Reddy, C., Rohit, M.V., Kumar, A.N., Sarkar, O., 2016. Waste biorefinery models towards sustainable circular bioeconomy: Critical review and future perspectives. Bioresour. Technol. 215, 2–12. doi.org/10.1016/j.biortech.2016.03.130

Vilanova Plana, P. and Noche, B. (2016). A review of the current digestate distribution models: storage and transport. Waste Manage 202, pp.345-357. doi: 10.2495/WM160311

Vondra, M., Masa, V., Bobak, P., 2016. The potential for digestate thickening in biogas plants and evaluation of possible evaporation methods. Chem. Eng. Trans. 787–792. doi.org/10.3303/CET1652132

Vondra, M., Máša, V., Bobák, P., 2018a. The energy performance of vacuum evaporators for liquid digestate treatment in biogas plants. Energy, Process Integration for Energy Saving and Pollution Reduction – PRES 2016 146, 141–155. doi.org/10.1016/j.energy.2017.06.135

Vondra, M., Masa, V., Tous, M., Konecna, E., 2018b. Vacuum evaporation of a liquid digestate from anaerobic digestion: a techno-economic assessment. Chem. Eng. Trans. 769–774. doi.org/10.3303/CET1870129.

Xia, A. and Murphy, J.D., 2016. Microalgal cultivation in treating liquid digestate from biogas systems. Trends Biotechnol., *34*(4), pp.264-275. doi: 10.1016/j.tibtech.2015.12.010

Zhang, Q., Hu, J., Lee, D.-J., 2016. Biogas from anaerobic digestion processes: Research updates. Renew. Energy 98, 108–119. doi.org/10.1016/j.renene.2016.02.029

Appendix

A. Full Decision Tree Diagram (Print Horizontally)

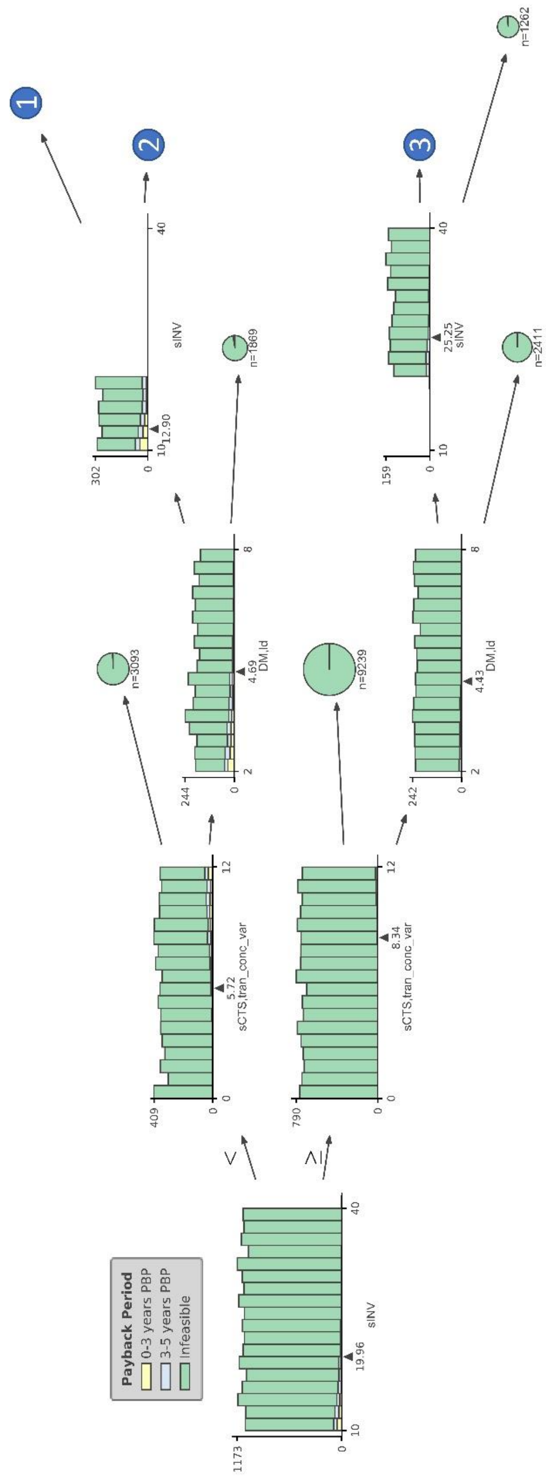


Figure A.1: Part 1 of the full decision tree classifier

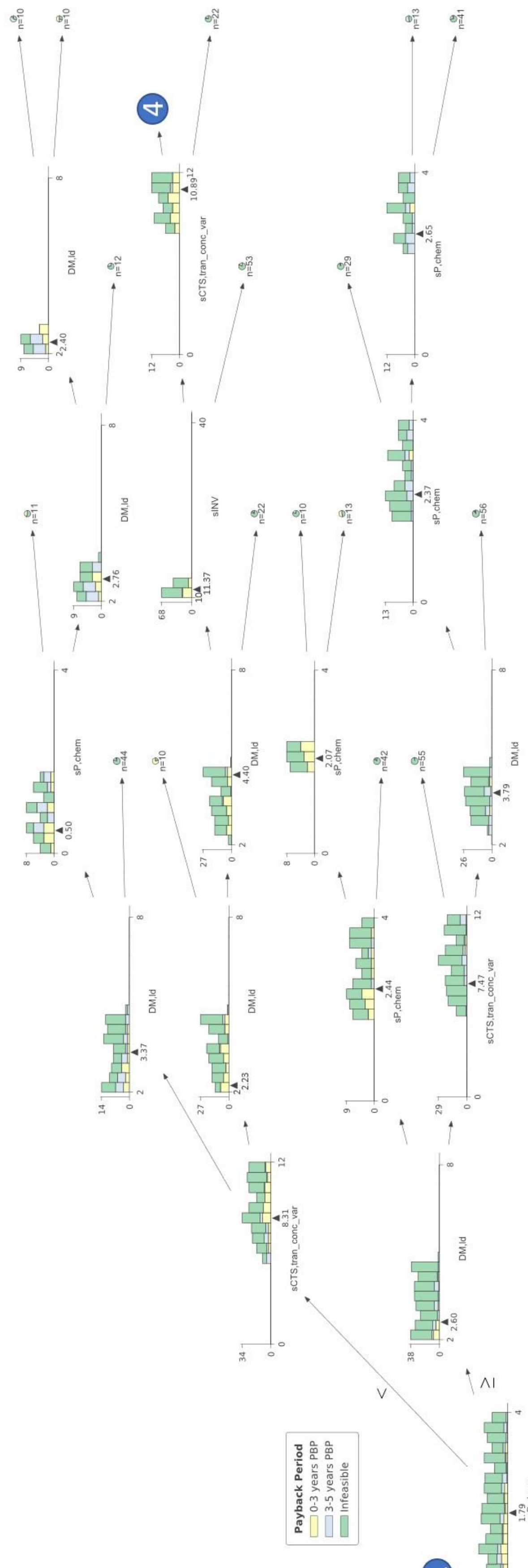


Figure A.2: Part 2 of the full decision tree classifier

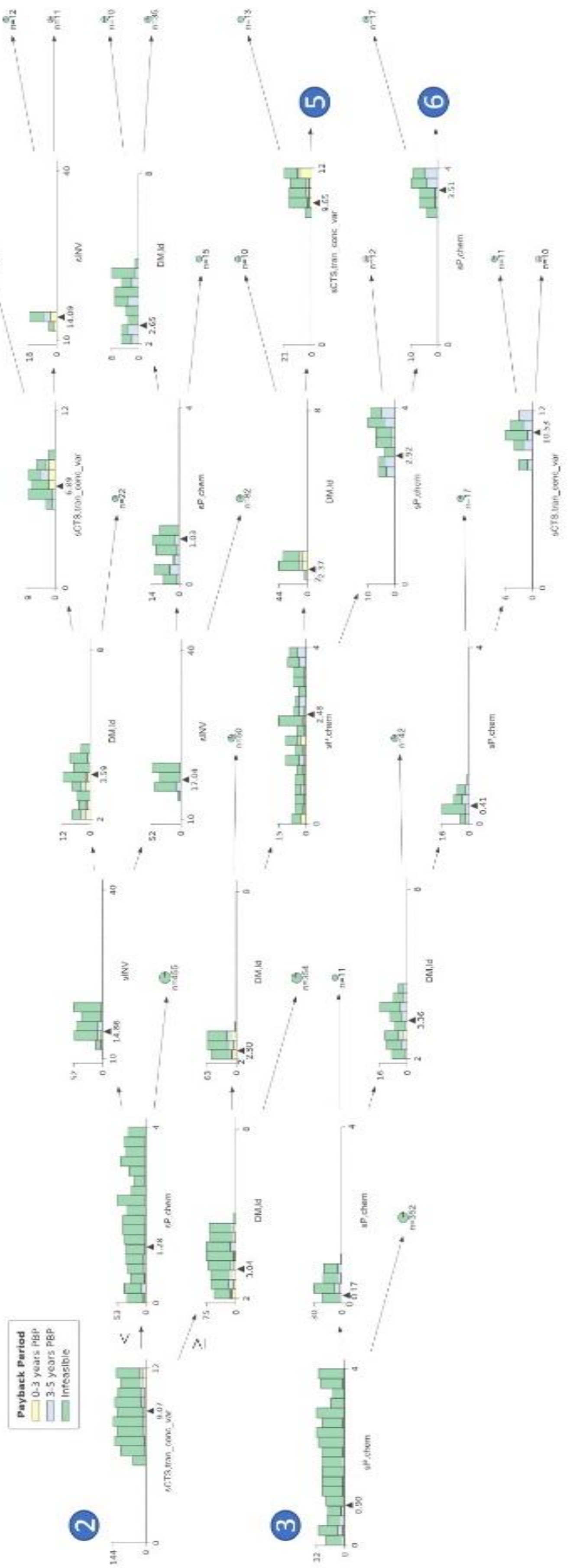


Figure A.3: Part 3 of the full decision tree classifier

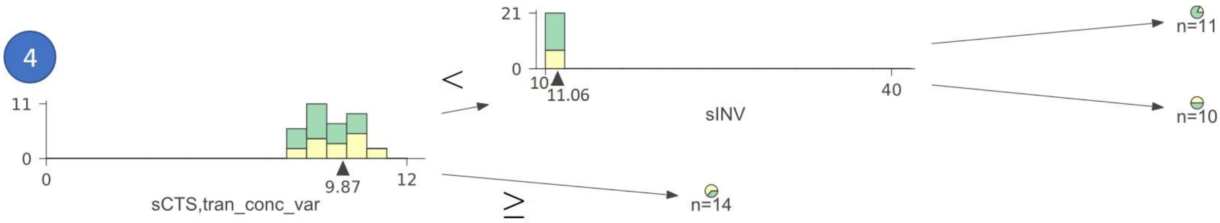


Figure A.4: Part 4 of the full decision tree classifier

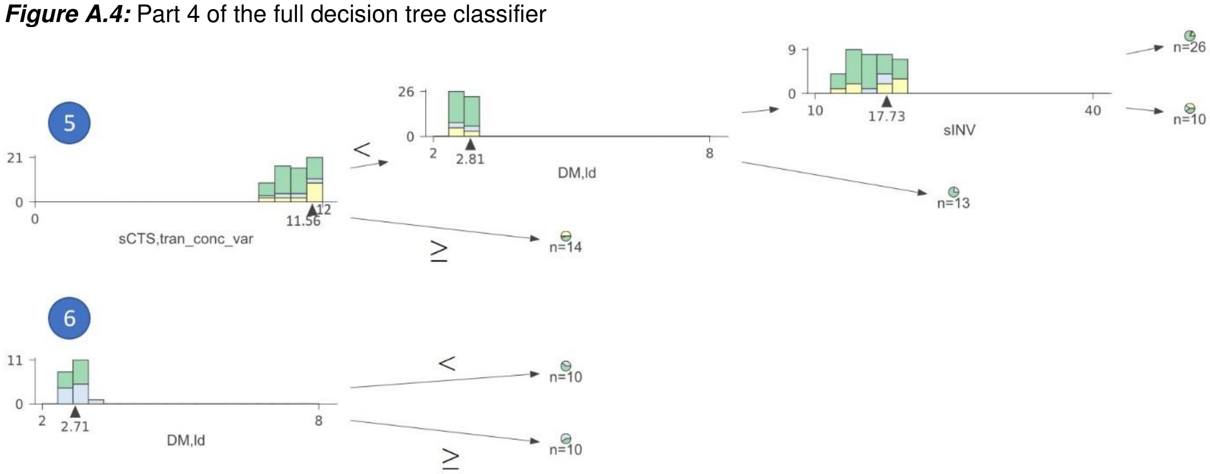
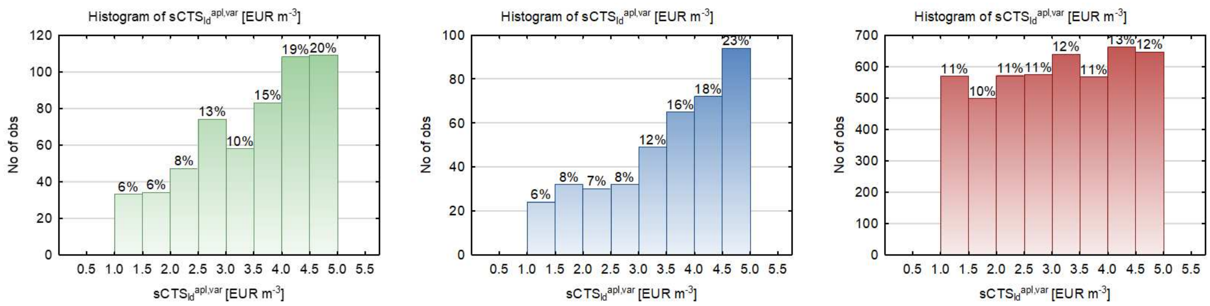


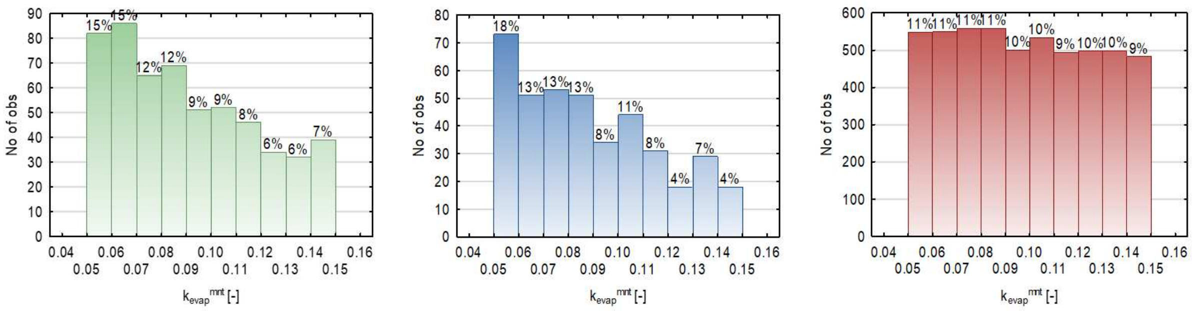
Figure A.5: Part 5 of the full decision tree classifier

B. Histograms for the "rules-based" datasets



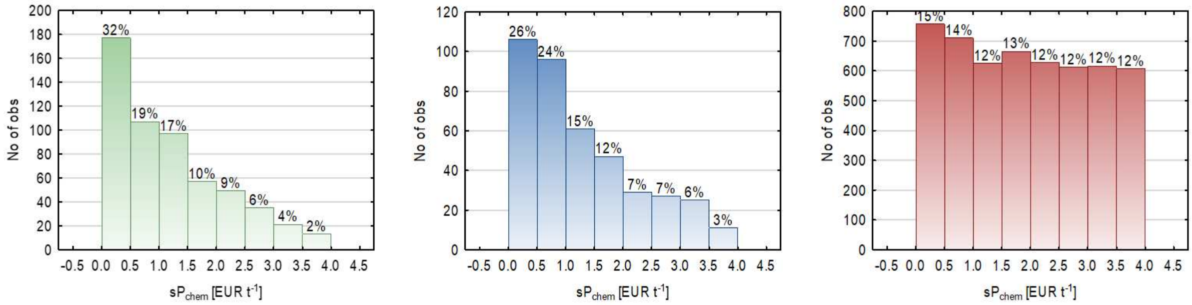
(a) **(b)** **(c)**

Figure B.1: Distribution of specific costs for LD application (spreading) in successful scenario of (a) "Base case 2" (b) "No ASS sale" (c) "CHP bonus" incentives



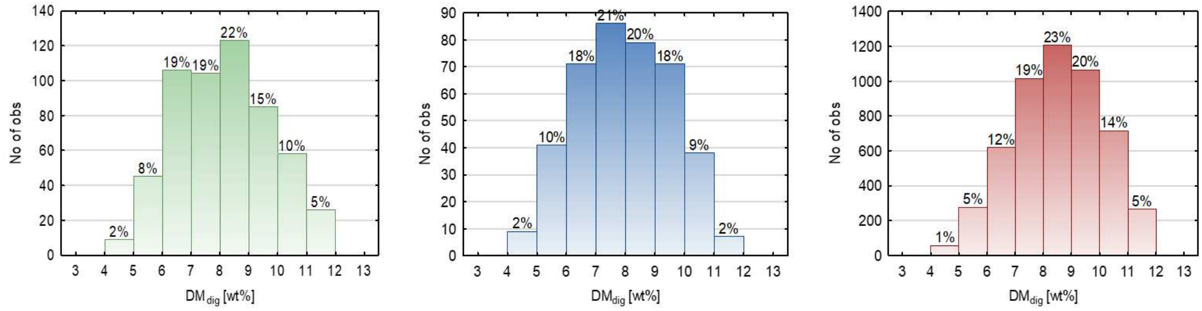
(a) **(b)** **(c)**

Figure B.2: Distribution of values of the maintenance coefficient in successful scenario of (a) "Base case 2" (b) "No ASS sale" (c) "CHP bonus" incentives



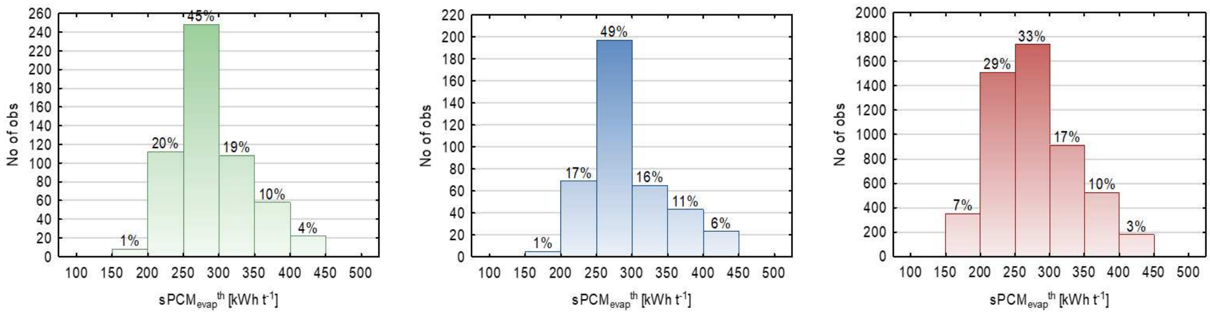
(a) (b) (c)

Figure B.3: Distribution of the specific price of chemicals in successful scenario of (a) “Base case 2” (b) “No ASS sale” (c) “CHP bonus” incentives



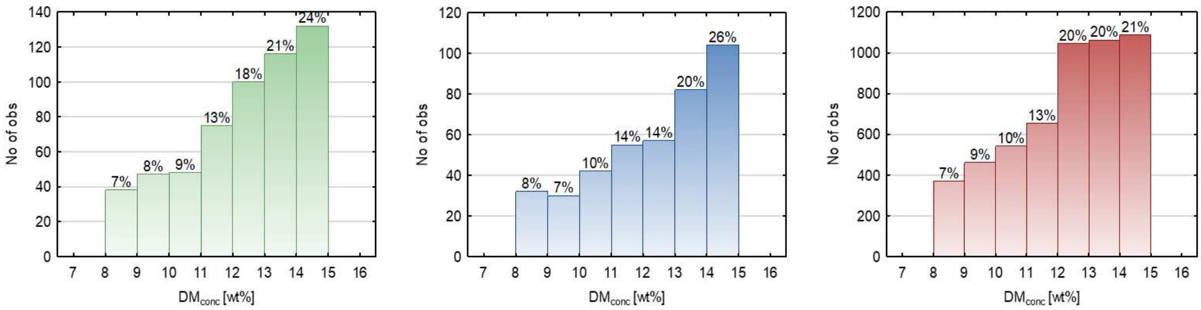
(a) (b) (c)

Figure B.4: Distribution of dry matter concentration in digestate in successful scenario of (a) “Base case 2” (b) “No ASS sale” (c) “CHP bonus” incentives



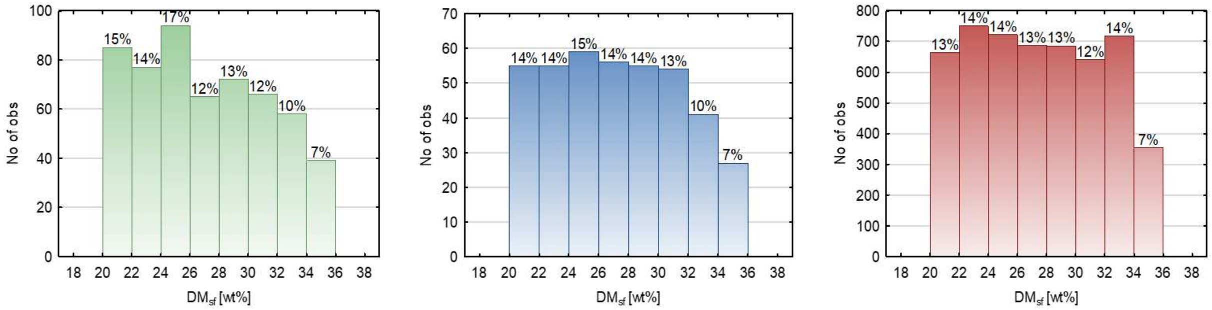
(a) (b) (c)

Figure B.5: Distribution of specific thermal energy consumption of an evaporation system in successful scenario of (a) “Base case 2” (b) “No ASS sale” (c) “CHP bonus” incentives



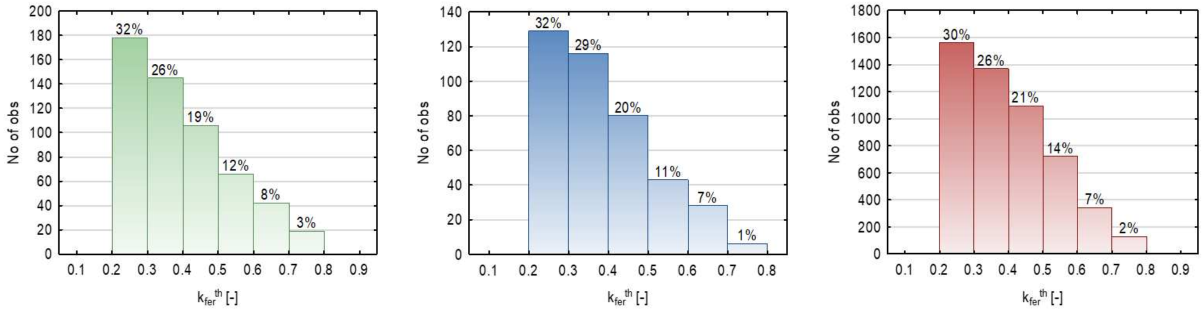
(a) (b) (c)

Figure B.6: Distribution of dry matter concentration in concentrated (thickened) LD in successful scenario of (a) “Base case 2” (b) “No ASS sale” (c) “CHP bonus” incentives



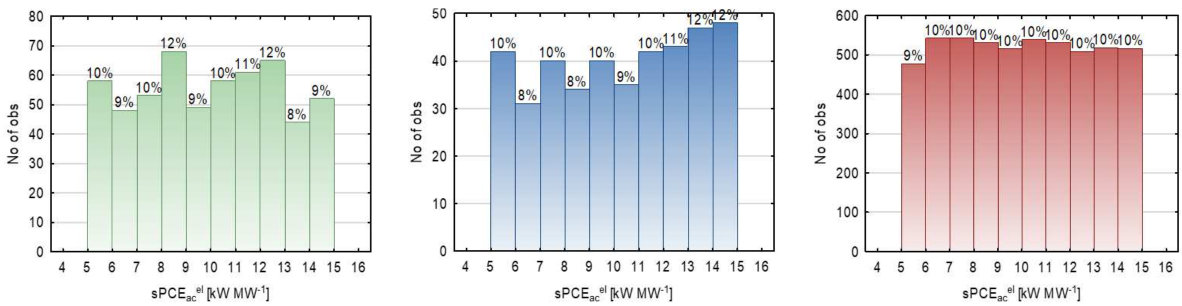
(a) (b) (c)

Figure B.7: Distribution of dry matter concentration in solid fraction of digestate in successful scenario of (a) “Base case 2” (b) “No ASS sale” (c) “CHP bonus” incentives



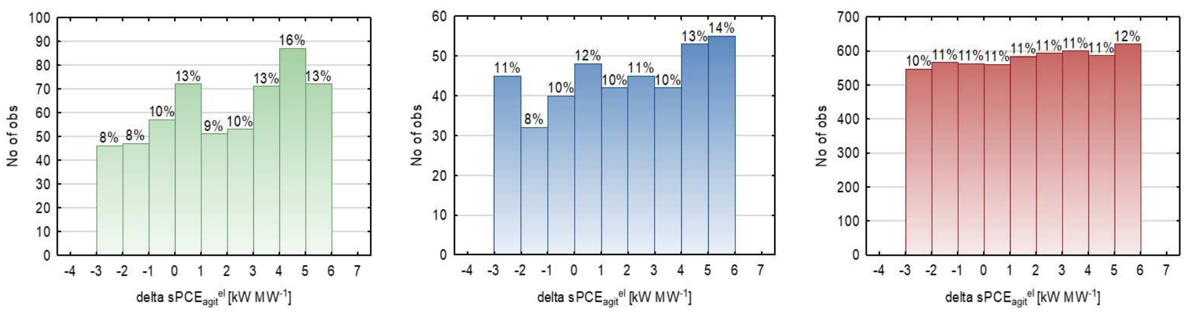
(a) (b) (c)

Figure B.8: Distribution of the coefficient of heat consumption in successful scenario of (a) “Base case 2” (b) “No ASS sale” (c) “CHP bonus” incentives



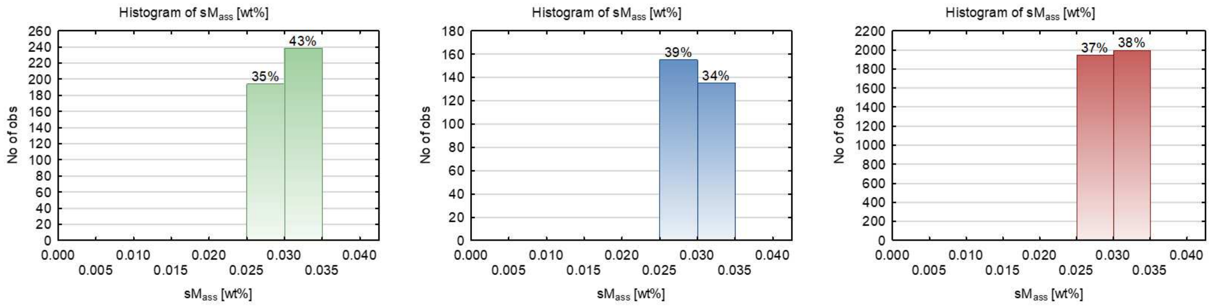
(a) (b) (c)

Figure B.9: Distribution of specific electricity consumption of air-cooled chillers in successful scenario of (a) “Base case 2” (b) “No ASS sale” (c) “CHP bonus” incentives



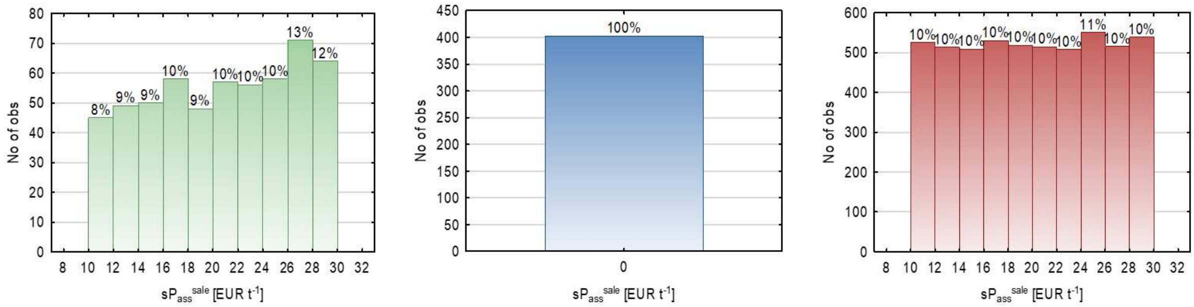
(a) (b) (c)

Figure B.10: Distribution of the change in specific electricity consumption of agitators in successful scenario of (a) “Base case 2” (b) “No ASS sale” (c) “CHP bonus” incentives



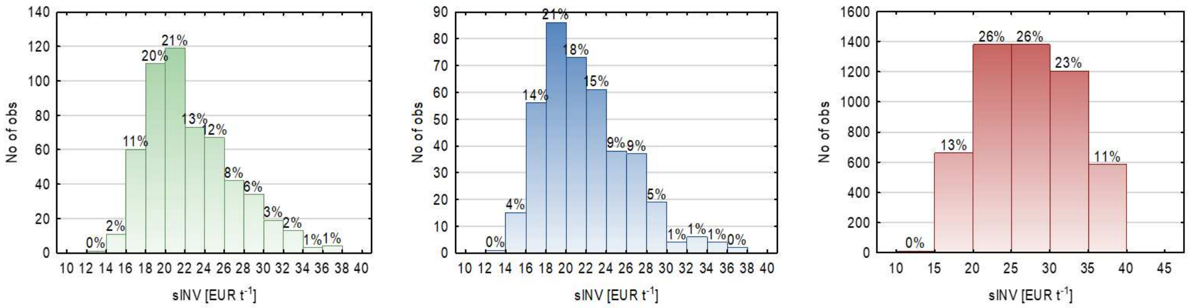
(a) (b) (c)

Figure B.11: Distribution of specific production of ammonium sulphate solution in successful scenario of (a) “Base case 2” (b) “No ASS sale” (c) “CHP bonus” incentives



(a) (b) (c)

Figure B.12: Distribution of specific market price for ammonium sulphate solution in successful scenario of (a) “Base case 2” (b) “No ASS sale”- not relevant (c) “CHP bonus” incentives



(a) (b) (c)

Figure B.13: Distribution of specific investment cost for an evaporation system successful scenario of (a) “Base case 2” (b) “No ASS sale” (c) “CHP bonus” incentives