Tampere University of Applied Sciences

Sustainability Assessment framework for comparing renewable energy investments

Holistic integration of environmental, economic, and social impact criteria

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ABSTRACT

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In the global energy transition to clean energy, it is imperative that renewable energy investments are assessed not only for their economic viability but also the environmental and social impacts. This research introduces a Sustainability Assessment (SA) framework designed to compare investments by combining all three pillars of sustainability. A thorough literature review is conducted to learn from already existing methods, define shortcomings and identify necessary improvements. In total 9 impact categories are proposed, all essential for a holistic SA framework. The chosen method for integrating multiple, non-comparable criteria is Multi-Criteria Decision Analysis (MCDA). By the means of weighing and normalizing, Analytical Hierarchy Process (AHP) holistically integrates 21 different criteria into a single comparable sustainability index. Based on the SA framework, a tool is developed that compares energy investment scenarios.

For tool's validation, a case study is performed on a 1GW offshore wind compared to a 1GW onshore wind farm and a 50MW photovoltaic solar farm. Life Cycle Assessment (LCA) results indicate that offshore wind farm has with a lower Global Warming Potential of 3.6gCO_2eq per kWh and a quicker Energy Payback Time (EPBT) of 6.1 months compared to onshore wind and solar alternatives. Financial assessment highlights the offshore wind farm's higher upfront costs and extended payback time, while having the most expensive Levelized Cost of Electricity (LCOE) of 0.051€/kWh, as compared to 0.038€/kWh for solar, and 0.027€/kWh for the onshore wind farm. Public acceptability surveys favour solar farm with 79% locals in support, as compared to the 74% for offshore and 63% support for onshore wind farm. As the study culminates, the SA framework distinctly positions the 1GW Gulf of Riga offshore wind farm as the most sustainable option, balancing environmental efficacy with respectable financial viability and societal support.

The study-case proves tool's applicability to various technologies and different capacities, showcasing impressive adaptability to any scenario. SA framework enhances sustainable decision-making in the renewable energy sector by providing stakeholders viable quantitative arguments for future investments. The tool will play a key role in guiding companies towards a more environmentally cleaner, economically feasible, and socially responsible future.

Key words: sustainability assessment, renewable energy, analytical hierarchy process, life cycle assessment, multi-criteria decision analysis

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ABBREVIATIONS

AHP	Analytic hierarchy process
ECHR	European Convention on Human Rights
IEA	International Energy Agency
IPBT	Investment Payback Time
kWh	Kilowatt-hour
LCA	Life Cycle Assessment
LCIA	Life Cycle Impact Assessment
LCOE	Levelized Cost of Energy
MCDA	Multi-criteria decision analysis
MW	Megawatt
PV	photovoltaic
SA	Sustainability Assessment
SLCA	Social Life Cycle Assessment

1 INTRODUCTION

The global pursuit of renewable sources of energy has become an increasingly supported strategy in addressing climate change and ensuring a reliable energy supply. One of the most notable technologies in the transition to a clean energy grid is solar and wind energy. In addition to the clean electricity, they diversify electrical systems and enhance the reliability of energy supply. As a result, investments in solar and wind power projects have increased exponentially.

The world has made tremendous progress in transition towards a cleaner energy grid. According to International Energy Agency (2022), solar energy production worldwide exceeded 1000 TWh for the first time in 2022. Whereas wind remains the leading non-hydro renewable technology, generating as much as all the other renewable energy sources combined. However, even these clean electricity production technologies have an environmental impact on their own. As the renewable energy systems become the most deployed energy sources worldwide, their environmental impact should not be disregarded. It is imperative that stakeholders not only focus on the economic viability, but also take into consideration the environmental and social impacts from raw material extraction to manufacturing and construction of the energy project.

Currently, there is a lack of clarity on how to holistically balance all three pillars of sustainability - environmental, financial, and social – in renewable energy investments. One of the most prominent studies on such a framework's development was created by Santoyo-Castelazo and Azapagic in 2014 for the Mexican government of future electricity supply scenarios. However, their approach is subjective as the chosen impact criteria intentionally aligned with the case study purposes. A more objective sustainability assessment framework was created by Buchmayr et al. in 2021, in the process reviewing 156 studies associated with energy sustainability. Yet their framework targeted all energy systems – renewable or not, hence various impact criteria can be omitted in a solely renewable energy-targeted framework. Furthermore, none of the studies offered a practical tool that can be used by companies in future renewable energy projects.

This gap hinders informed decision-making in the renewable energy sector, as investors still mainly focus on the economic viability of the projects, while disregarding environmental or social aspects. This framework aims to fill this void and provide a practical tool for making sustainable investment decisions in renewable energy projects. By analysing environmental, economic, and social criteria, future projects will have more viable arguments for their long-term sustainability.

The research follows a systematic approach, combining a comprehensive and thorough literature review on existing studies, tool development, data collection, and finally tool validation by assessing the sustainability of a case-study. The following research questions will dictate this study process:

1. How can a comparative analysis framework combine and compare environmental, economic, social factors in renewable energy investments?
2. What key criteria should be considered in the comparative assessment for more holistic sustainable investment decisions?
3. How effectively does the tool provide arguments for decision-makers, when used in a real-world investment project?

The subsequent chapters of this thesis will delve into the development of the comparative framework, then comprehensive tool creation, and the application on a historically significant wind energy investment in Estonia – first ever off-shore wind farm in the Baltic States developed by Enefit Green. This analysis helps companies like Enefit Green avoid suboptimal choices, ensuring efficient resource allocation while reducing environmental and financial risks. By systematically comparing investment scenarios, companies can make more informed and sustainable choices for their future projects.

2 SUSTAINABLITY ASSESSMENT FRAMEWORK

The purpose of a sustainability assessment is to analyse how sustainable a project is not only from the environmental, but also economic and social viewpoint. In the process it can be compared to another energy production scenario to evaluate which one is more sustainable in the long-term. However, integrating all three pillars of sustainability into a holistic assessment framework is not as straightforward as it seems.

Different units from environment to economic analysis, varying scopes, subjectivity makes it difficult to objectively assess a project's sustainability. There have been numerous developments of a sustainability assessment framework in the past. From the first significant "*Model of energy economic interactions*" by Meier and Mubayi back in 1983, to more recent case studies by Santoyo-Castelazo and Azapagic designing a "*Sustainability framework of future electricity supply in Mexico 2050*". Yet none of the methods offer a generalized criteria selection, which can be applied to any scenario.

2.1 Methodology

This research employs a mixed-methods approach to develop and evaluate a sustainability assessment (SA) framework. This approach ensures an objective and comprehensive evaluation of renewable energy investments, considering all three pillars of sustainability. Objectivity in framework development is of highest priority for compatibility and application in future SA comparisons.

Firstly, a thorough literature review is conducted on already existing studies of such frameworks. Studies and publications were indexed in Google Scholar in keywords: ("energy" AND "sustainability" AND "assessment") OR ("Renewable energy investment" AND "assessment framework"), published from 2013 to 2023. The objective of this review is to identify via content analysis the most used methods, approaches, data sources and tools for sustainability assessment of energy systems. The review identifies key environmental, economic, and social impact categories and criteria for inclusion in the framework.

Criteria selection is solely on the literature review. Quantification methods for each impact category are determined, considering their relevance and applicability. These methods include life cycle assessment (LCA) for environmental criteria, economic modelling for economic criteria, and public questionnaires for social criteria. Data sources for impact category quantification are identified, for example, OpenLCA software for environmental LCA and financial databases for economic data. The sustainability assessment framework is developed based on the selected impact categories and quantification methods, finally creating a structured tool for comparing energy investment scenarios.

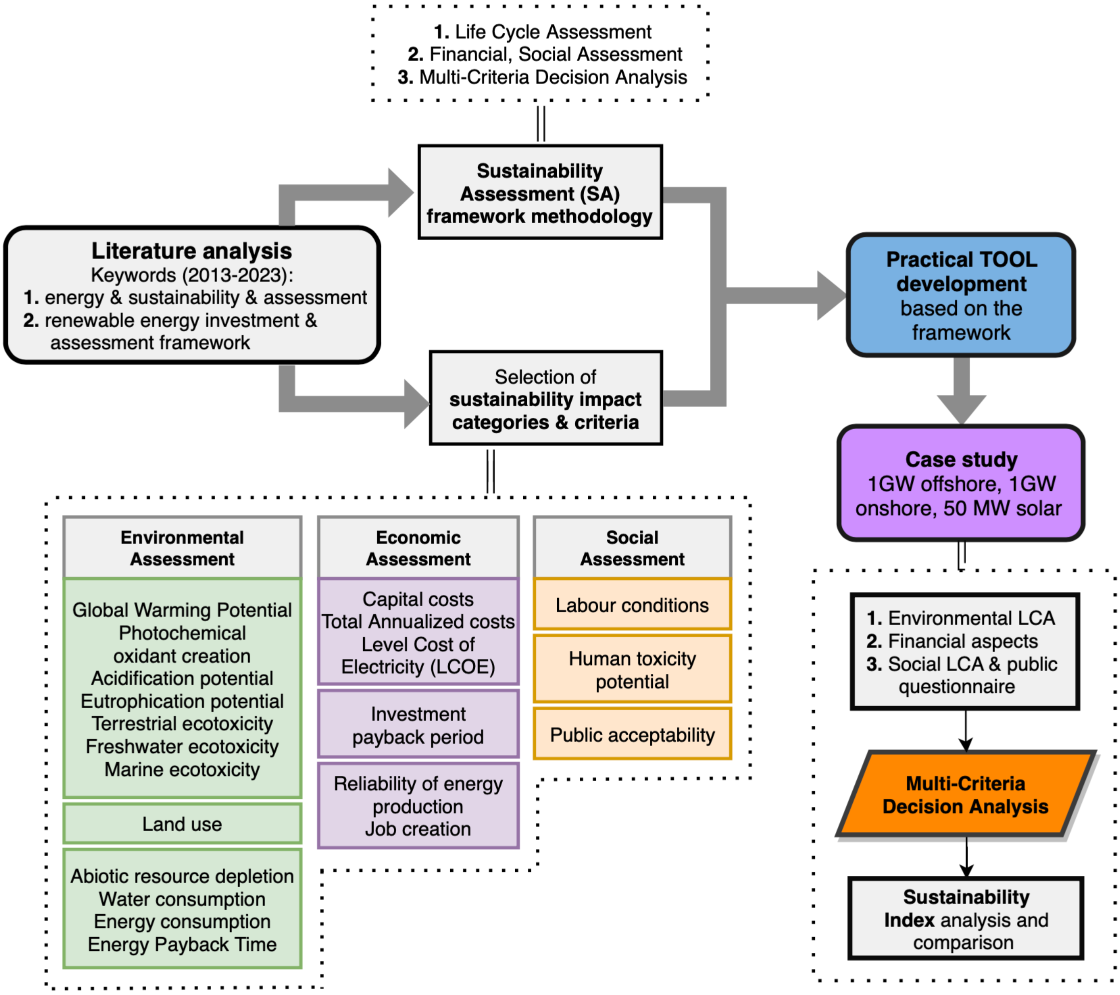


FIGURE 1. Systematic process flow of this research.

To ensure the applicability of the created sustainability assessment framework, a practical tool is developed in Google Sheets for public use. For tool validation, a case study is performed – “The Gulf of Riga Offshore wind farm”, first ever offshore wind farm in the Baltics, with the total power output of 1 gigawatt (1000MW). Historically largest renewable energy investment in the Baltic States, it is a perfect case study for the application of this SA framework.

For environmental criteria, a Life Cycle Impact Assessment (LCIA) is performed using OpenLCA software. For economic criteria, publicly available data is used, as well as economic analysis using mathematical functions in Excel. Finally, for social impact, a public questionnaire is performed, results of which are compared to the company’s statement about public support. Data from the criteria impact assessment is integrated using Analytical Hierarchy Process (AHP), which derives normalized and weighted indicator values, enabling the integration of various criteria units into a unified assessment unit: sustainability index.

Finally, Enefit Green 1000MW offshore wind farm’s sustainability index is compared to two hypothetical scenarios: 1000MW onshore wind farm, and 50MW solar farm. Based on the quantitative results of the analysis, actionable recommendations are provided to the company. The technical challenge of this case study will test tool’s objectivity, ease-to-use, and comprehensiveness.

The study concludes with a discussion of the framework's effectiveness, limitations, and potential applications. The framework is developed with the intention of use in future renewable energy investments.

2.2 Existing approaches

One of the most prominent examples is a study performed by Santoyo-Castelazo and Azapagic in 2014, creating a sustainability framework to analyse the sustainability of future energy production in Mexico 2050. They realised that even with the Mexican Government’s attempts reduce greenhouse gas (GHG) emissions with renewable energy investments, they would still not reach 2050 climate goals. Hence, more sustainable, and realistic options for future electricity supply had to be identified. Their approach studied eleven different scenarios, considering different technologies and electricity mixes (by percentage of production) to see which ones are the most sustainable options. The framework integrated environmental, economic, and social aspects holistically, identifying most sustainable options for the government. The integration of all three pillars of sustainability with varying units was done by Multi-Criteria Decision Analysis. (Santoyo-Castelazo & Azapagic 2014).

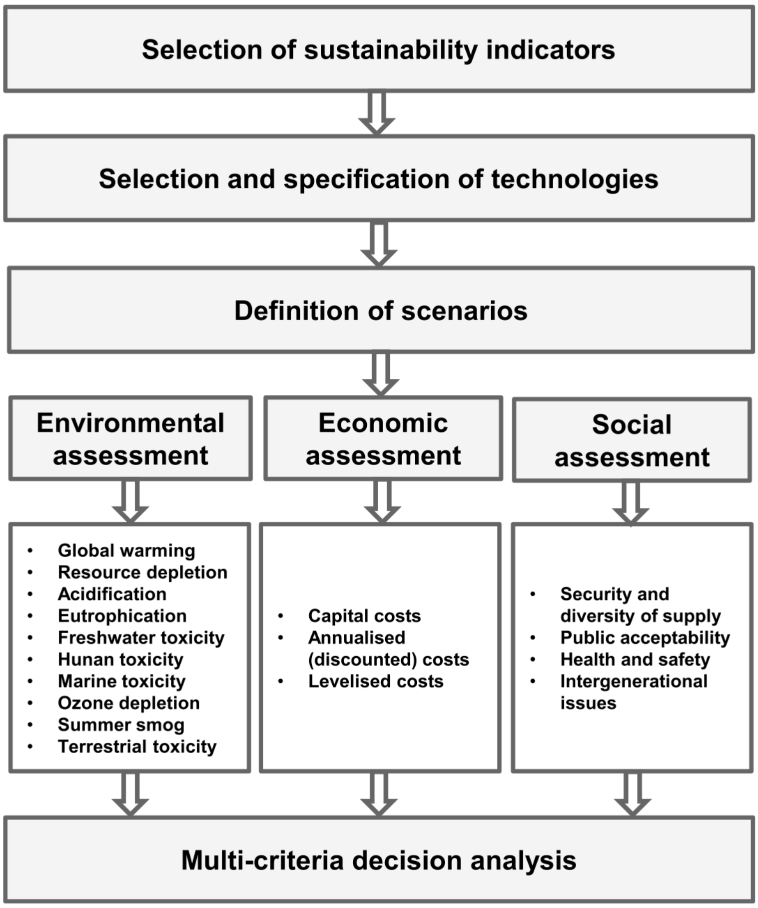


FIGURE 2. Framework for integrated sustainability assessment of energy systems (Santoyo-Castelazo & Azapagic 2014).

Based on the assessment of the 17 proposed sustainability impact criteria, they compared different energy production scenarios. Their results indicated possible electricity production mixes that would achieve the Mexican GHG emission targets by 2050 in the most sustainable approach - from environmental, economic, and social way way. (Santoyo-Castelazo & Azapagic 2014).

Considering the SA framework created in the study, it appears to be universally applicable to any case-study. However, the MCDA method of choice is arbitrary when compared to other methods. An additional argument could be made that this approach is subjective towards the needs of the study. Even though Santoyo-

Castelazo and Azapagic state that the chosen impact criteria were chosen based on previous research papers, it is not elaborated enough on their objectivity and applicability in other case-studies.

This issue is common in SA framework literature, as another study performed by Abu-Rayash & Dincer (2019) used different sustainability assessment criteria: energy, exergy, economy, environment, society, technology education, and size of the energy system. Their approach aimed to be more objective than the one proposed by Santoyo-Castoyo and Azapagic. However, the high num-ber of sustainability indicators could cause possible double-counting the im-pacts. Because the impact categories are similar, quantifying the impacts in a proper way is challenging. For example, economy, society, and technology education are affected by each other in the scope of the life cycle, hence more individual and inert impact criteria are necessary.

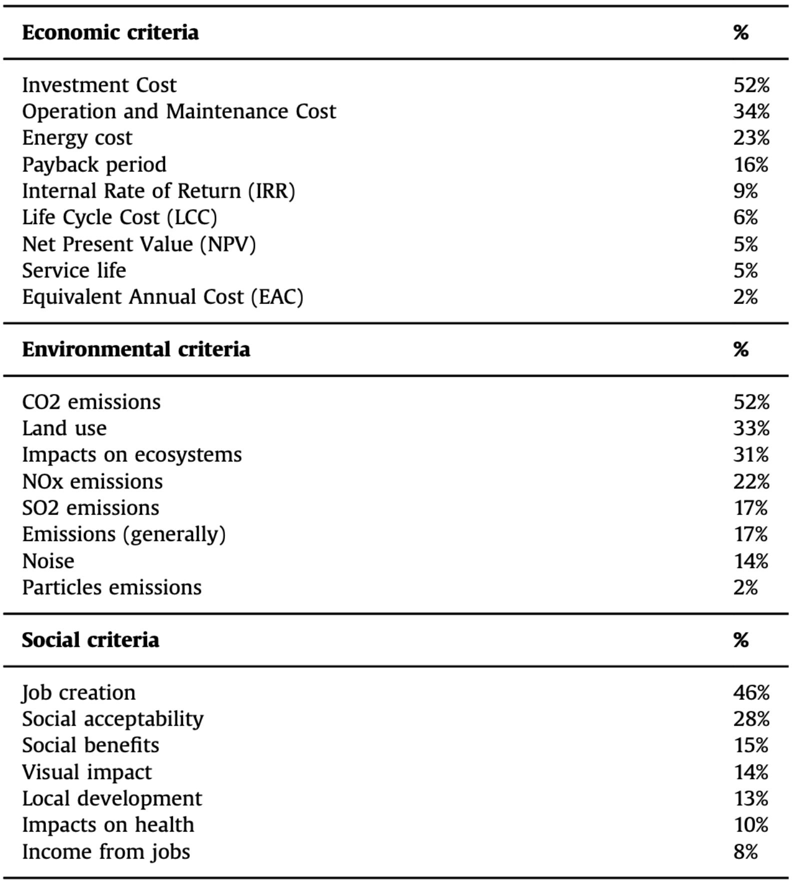
2.3 Criteria selection

The literature offers a wide array of SA frameworks, yet there is not a consensus on which impact criteria should be considered in a generalized impact assessment. While certain aspects, like the environmental impact of emissions, always receive substantial attention, social and economic impacts often lack adequate analysis. This shortcoming has motivated several studies compiling which environmental, economic, and social criteria are used most frequently. Two most prominent study review papers are analysed:

- “Decision making in renewable energy investments: A review.” (Strantzali, & Aravossis 2016). Review of 183 publications on energy investments, analysing most used sustainability criteria.
- “The path to sustainable energy supply systems: Proposal of an integrative sustainability assessment.” Literature review of 32 most relevant Sustainability Assessment studies, in the process proposing a universal SA framework. (Buchmayr et al. 2021).

These two study reviews are most thorough literature review publications on the topic of Sustainability Assessment Framework. Because one was done on specifically on renewable energy investments and the other on all energy types – it is expected that proposed criteria might vary due to different research subjects. The most objective way to proceed is to review and compare their criteria selections, finally combining them into one holistic set of impact criteria.

In 2016, Strantzali & Aravossis reviewed nearly two hundred studies concerning the methodology and decision-making approaches in renewable energy. The review not only offered a statistical analysis of used methodology, but also most used criteria in SA frameworks by percentage.



Economic criteria	**%**
Investment Cost	52%
Operation and Maintenance Cost	34%
Energy cost	23%
Payback period	16%
Internal Rate of Return (IRR)	9%
Life Cycle Cost (LCC)	6%
Net Present Value (NPV)	5%
Service life	5%
Equivalent Annual Cost (EAC)	2%

Environmental criteria	**%**
CO2 emissions	52%
Land use	33%
Impacts on ecosystems	31%
NOx emissions	22%
SO2 emissions	17%
Emissions (generally)	17%
Noise	14%
Particles emissions	2%

Social criteria	**%**
Job creation	46%
Social acceptability	28%
Social benefits	15%
Visual impact	14%
Local development	13%
Impacts on health	10%
Income from jobs	8%

FIGURE 3. Decision making in renewable energy investments. Classification and percentage of criteria by reviewing 183 publications on renewable energy investments. (Strantzali & Aravossis 2016).

A similar study was done by Buchmayr et al. (2021), making objectively similar conclusions after reviewing 32 sustainability assessment studies. Interestingly, they concluded that all criteria can be separated into 12 specific categories: Emission damage, Land use, Resource use efficiency, Resource depletion, Energy supply reliability, Technology characteristics, Resource supply risk, Economic feasibility, Job creation, Human rights, Labour conditions, Health and Safety, Residential life, Landscape quality.

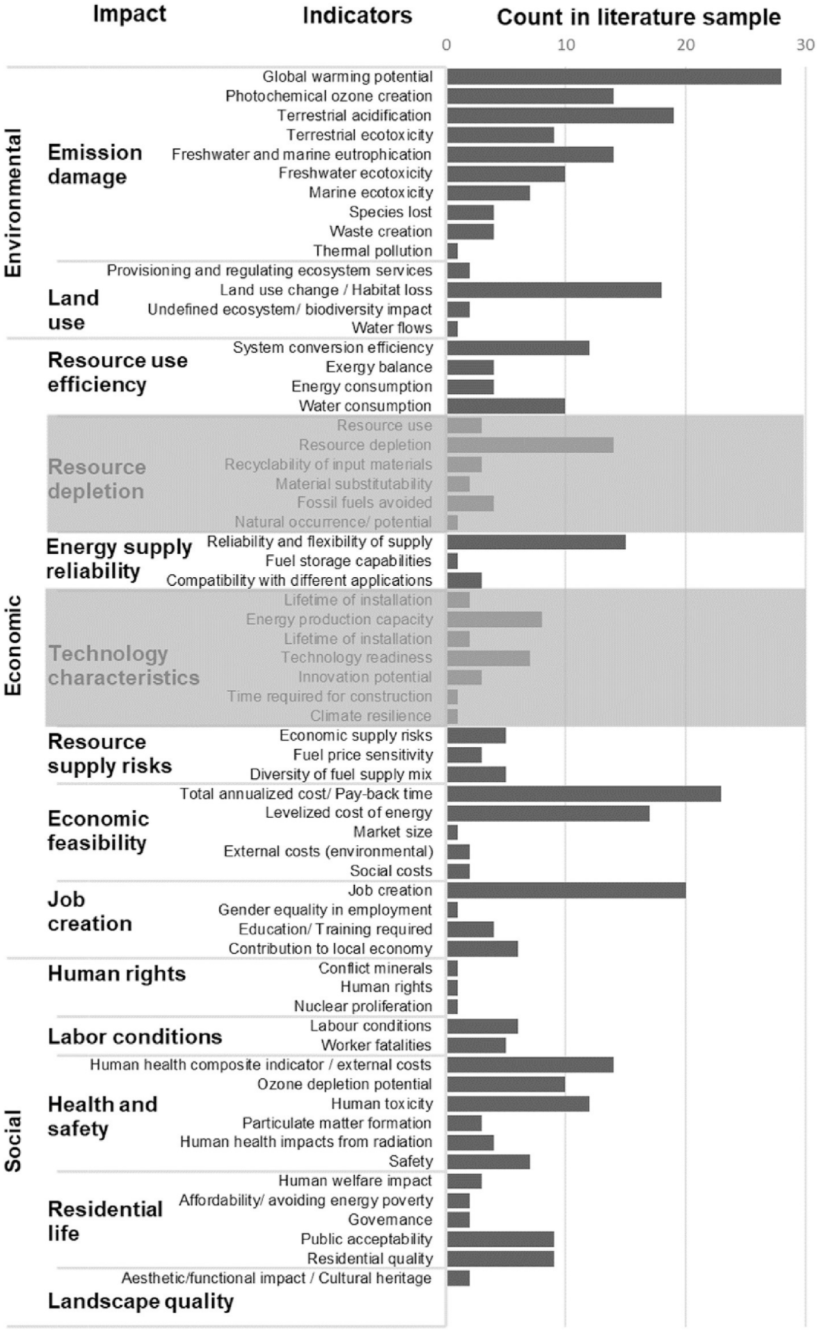


FIGURE 4. Categorization of sustainability criteria compiled from reviewing 32 sustainability assessment studies (Buchmayr et al. 2021).

Since the review focused on all types of energy investments (oil, gas, renewables), then a few of these can be neglected in a solely Renewable energy-based assessment framework. For example, "resource supply risks" measures how much a coal plant is affected by possible coal supply risks. This would not be applicable in the case of renewable energy.

Impact criteria for this framework were chosen by comparing and compiling both reviews. Strantzali & Aravossis' review provided a compilation of 27 different criteria, however, Buchmayr et al. offered more than 50 unique ones. Almost half of these are most likely niche case-study-based assessments, making them subjective and not applicable in this framework. Even though the compiled criteria in both reviews do not match by their labels, most of them can be associated by categorization.

The chosen criteria were among the most common, most applicable, objective, and best measurable ones from the two reviews. The proposed impact criteria selection combines all the most important criteria into nine different categories, three in each of the main pillars of sustainability assessment:

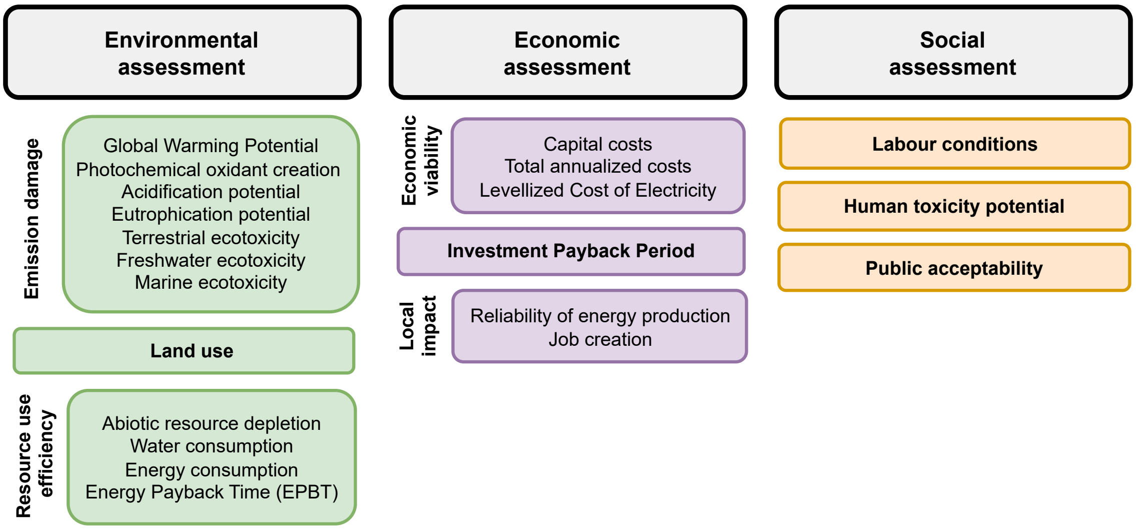


FIGURE 5. Sustainability assessment impact criteria based on review papers.

The selected criteria are all objective and measurable with existing methods and software. Some impact criteria would have very appropriate for the framework but were emitted due to limited methods in quantifiable assessment. For example, "*Residential life impact*" or "*Landscape quality impact*", would have been perfect sub-criteria in measuring how much the project affects locals and tourism. Unfortunately, there are no proposed methods to quantifying this, hence they are not included in social assessment criteria selection.

The following subchapters provide detailed explanation of each criterion, providing assessment methods, units, recommended software and practical study papers, which can be used as a reference for measuring the impact criteria.

2.4 Environmental Impact Assessment

Economic viability is always given higher priority in investments by companies – especially in renewable energy, which is considered “clean” and not associated with any environmental footprint at all. As solar and wind power becomes most deployed sources of electricity in the future, exceedingly more rare earth metals, steel and concrete production is expected. The environmental impacts should not be disregarded. Being the first association when discussing sustainability of a construction project, environmental impact assessment is an important pillar of the SA framework.

Three environmental impact categories were proposed based on the reviews:

1) *Emission damage*
2) *Land use*
3) *Resource use efficiency*

Even though there are many important sub-criteria that should be present in this list, such as *“Global Warming Potential”* or *“Terrestrial acidification potential”*, these and many more share a common endpoint, which is, damage due to emissions. Combining the sub-criteria into these three categories enables a simplified approach in environmental assessment.

2.4.1 Emission damage

Seven sub-criteria are characterized as “*Emissions damage*”. Descriptions of criteria provided by Ecochain (2023):

1. **Global Warming Potential**: a measure that quantifies the overall heat-trapping impact of greenhouse gases released during the entire lifecycle

of an energy project. It is expressed in terms of the equivalent amount of carbon dioxide (CO_2) that would produce an equivalent warming effect. The unit of measurement for GWP is typically grams of CO_2-equivalent per kilowatt-hour (gCO2-equivalent per kWh).

2. **Photochemical Oxidant Creation**: the potential of the formation of ground-level ozone, expressed in terms of the potential for creating ozone compared to ethene (mgC_2H_4eq /kWh).
3. **Acidification potential**: the impact of the energy project on the acidification of terrestrial ecosystems, as compared to sulphur dioxide (SO_2) with the same effect ($mgSO_2eq$ /kWh).
4. **Eutrophication potential**: the potential contribution to nutrient enrichment in water bodies, leading to excessive plant growth, expressed in potential for causing as much eutrophication as phosphate ($mgPO_4eq$ /kWh).
5. **Terrestrial ecotoxicity**: a measure of the potential harm to terrestrial ecosystems, measured in milligrams of 1,4-dichlorobenzene equivalent per kilowatt-hour (mg1,4-DBeq /kWh).
6. **Freshwater ecotoxicity**: the potential harm to freshwater ecosystems, based on 1,4-DBeq toxicity to aquatic organisms (mg 1,4-DBeq /kWh).
7. **Marine ecotoxicity**: the potential harm to oceanic environments and marine ecosystems during the lifecycle of an energy project. Like terrestrial and freshwater ecotoxicity, it is expressed in milligrams of 1,4-dichlorobenzene equivalent per kilowatt-hour (mg 1,4-DBeq/kWh).

Calculated impact is averaged per the entire produced energy (kWh) over the system's operational lifetime. This prioritizes the energy system's efficiency, that is, even if the environmental impact in the manufacturing process is significant, it is averaged per how much energy the system will produce in its lifetime. This approach enables the comparison between different total project capacities. Additionally, this unit enables comparison between other studies.

Life Cycle Assessment calculates the environmental impacts of a product or system during its entire lifecycle (Ecochain 2023). The accuracy of an LCA study relies on a detailed Life Cycle Inventory Assessment, which tracks all material and process flows that are required in manufacturing, constructing, and decommissioning of the energy project. The more detailed inventory assessment is, the more accurate results. It's recommended to perform LCA for the entire project lifecycle, maintaining system boundaries from cradle to grave.

Finally, Life Cycle Impact Assessment (LCIA) translates identified impacts into quantifiable environmental impacts. There are many quantification methods available for LCIA, yet ReCiPe method offers the most appropriate approach for SA of energy systems. ReCiPe2016 converts life cycle inventories into impact scores, which enable a clear and precise calculation scope for the LCIA. (Huijbregts et al. 2017).

There are multiple LCA software tools available: Simapro, Gabi Sphera, Ecochain Mobius, OneClick LCA, and OpenLCA. All of these enable the creation of a LCA based on case-specific data with scientific standards.

2.4.2 Land use

Land use is a crucial criterion for assessment of renewable energy projects as it directly impacts ecosystems, biodiversity, and local resident quality of life. In a thorough analysis, land transformation is calculated for the entire lifecycle of the energy project – raw material production, processing, manufacturing, construction, operation, and decommissioning. Methods in calculating land use include LCA methods (e.g. ReCiPe2016 or CML-IA), which can be combined with LCA study of "*Emission damage*". However, indirect land transformation is not easy to comprehend when comparing to the real world. For tool's applicability for companies, only direct land use is considered.

A compressive calculation of "*Land use*" is direct land use, which is the area of the project measured in km^2. Direct land use neglects LCA stage of raw material production, however, provides a more reliable value in direct calculations.

The calculation of the direct area of a project is usually done by using satellite imagery. However, in hypothetical scenarios this is not possible. Hence another way is proposed: Capacity Density factor, which is the technology's area per deployed capacity (km^2/MW). This factor is generally quite reliable in approximating how much area would the project use by knowing its total capacity of the project.

$$A_{direct} = P \cdot \nu \ , \tag{1}$$

where:

A_{direct} – direct land use of an energy project (km^2),
P – installed capacity of the project (MW),
ν – capacity density of energy technology (km^2/MW).

A thorough study of 16 onshore and 7 offshore windfarms concluded that offshore wind farms have a capacity density of 0.139 km^2/MW. Yet, onshore wind farms: 0.051 km^2/MW (Enevoldsen, P. & Jacobsen, M. 2021). However, photovoltaic ground-mounted solar farms on average have a capacity density of 0.102 km^2/MW (IEA 2022).

2.4.3 Resource use efficiency

Divided into five sub-criteria, resource use efficiency is a category meant for assessing the efficiency of the energy project.

1. **Abiotic resource depletion**: total consumption of natural resources, such as fossil fuels, in the whole life cycle of the project, measured in oil equivalent translated into energy mega-joules (MJ).
2. **Water Consumption**: the amount of water used in m^3, measured in direct and indirect impact on water resources (tons).
3. **Energy Consumption**: total amount of energy consumed in the lifecycle of a project, indicating the overall energy demand (MWh).
4. **Energy Payback Time (EPBT)**: the duration it takes for an energy system to generate the same amount of energy that was consumed in raw material extraction, its manufacturing, installation, operation, and decommissioning phases (unit: years).

EPBT provides insights into how long it takes for the energy benefits of a renewable system to offset the environmental costs associated with its entire lifecycle. A shorter EPBT generally indicates a more environmentally favourable energy source, as it implies quicker recovery of the initial energy investment.

By using the same boundaries and lifecycle inventory flows, these criteria are calculated with the same methodology as previously mentioned LCA. *Abiotic resource depletion* and *Water consumption* are calculated with the Cumulative Exergy Extraction from Natural Environment (CEENE) LCIA method. Based on the EcoInvent database, the CEENE calculates the amount of fossil fuels and water extracted from the environment. *Energy consumption*, however, is calculated with LCIA method “Cumulative energy demand”, which quantifies the energy consumption.

Finally, calculating EPBT can be done by reading manufacturer’s data sheet of the deployed model of solar panel or wind turbine. However, if there is no data available, then EPBT is calculated by the following equation:

$$EPBT = \frac{E_{consumed}}{AE} \, , \tag{2}$$

where:
$EPBT$ – energy payback time ($months$),
$E_{consumed}$ – total energy consumption in manufacturing and deployment (kWh),
$E_{monthly}$ – monthly produced energy ($\mathrm{MWh/month}$).

2.5 Economic Assessment

Several economic indicators are used to determine whether a project is worth the investment. Majority of these criteria are from the company’s perspective, lacking the analysis on economic impact outside. Because this renewable energy framework is meant for use of companies, the following criteria selection is appropriate. Economic assessment is divided into three parts: *Economic viability*, *Payback time*, *Local economic impact*.

2.5.1 Economic viability

Investment's viability covers various financial metrics from the initial investment to annual profit, to cost-effectiveness and cost of electricity. Assessment the overall feasibility of an investment is a crucial indicator for the company. Three subcriterion are categorised as part of economic viability in this SA framework: *Capital costs*, *Total annualized costs*, *Levelized Cost of Electricity (LCOE)*.

Capital costs, i.e. initial investment, comprises of all expenses in planning, construction, and installation of the energy project. Counting the initial investment is challenging, as every financial aspect should be considered. There is not a universal formula, as every case-study is different in its initial investment scenario. However, a simplified formula for energy investment capital cost is (IEA 2010):

$$TC_C = \sum C_C P \ , \tag{3}$$

where:
TC_C – total capital costs ($€$),
C_C – "overnight" capital costs of energy project ($€/\mathrm{MW}$),
P – installed capacity of the project (MW).

The total annualised cost includes the cost of owning, operating, and maintaining an energy project over its entire life (Santoyo-Castelazo & Azapagic 2014):

$$TAC = \sum AC_C + \sum F_C + \sum V_C \ , \tag{4}$$

where:
TAC – total annualised cost ($€/\mathrm{yr}$),
AC_C – annualised capital costs ($€/\mathrm{yr}$),
F_C – annualised fixed costs ($€/\mathrm{yr}$),
V_C – annualised variable costs ($€/\mathrm{yr}$).

The annual fixed costs (F_C) comprise of the costs of maintenance, staff costs, insurances, or repairs and taxes. The variable annual costs (V_C) expenses that are irregular, e.g. contracted personnel. The annualised capital costs (AC_C) are calculated by considering the total capital costs of the investment (TC_C), and an annuity factor (f). The following formula is used to calculate the depreciation of the project – it’s the loss in value of the capital (Santoyo-Castelazo & Azapagic 2014):

$$AC_C = TC_C \cdot f \tag{5}$$

$$f = \frac{z(1+z)^t}{(1+z)^t - 1}\ , \tag{6}$$

where:

AC_C – annualised capital costs ($€/\mathrm{yr}$),

TC_C – total capital costs ($€$),

f – annuity factor,

z – discount rate of the capital (%),

t – operational lifetime of the project (years).

Finally, the Levelized Cost of Electricity is a key criterion in comparing the cost-effectiveness of renewable energy investments. LCOE shows how cheap is the produced energy over the system's operational lifetime. In the energy investment industry, LCOE is considered to be of similar importance of return-on-invesment in any other industry. It is calculated by total project life cycle cost by the total energy generation over the operational lifetime (Emblemsvåg 2020):

$$LCOE = \frac{C_C + (TAC \cdot t)}{EA \cdot t}\ , \tag{7}$$

where:

$LCOE$ – levelized cost of electricity over the operational life cycle ($€/\mathrm{kWh}$),

C_C – investment capital costs ($€$),

TAC – total annualised cost ($€/\mathrm{yr}$),

t – operational lifetime of the project (years),

AE - annual energy generation (kWh/yr).

2.5.2 Payback time

Investment payback time (IPBT) is similar to *Energy payback time*; however, it is solely financially based. IPBT is the number of years required to recover the investment cost, based on the produced electricity and annual profit. Every renewable technology differs its energy production rate, therefore every investment scenario should be calculated on its own. General formula divides capital cost with annual financial return (Kessler 2017):

$$IPBT = \frac{TC_C}{(E_{annually} \cdot c_{elec}) - (TAC \cdot t)} \ , \tag{8}$$

where:

$IPBT$ – investment payback time (years),

TC_C – total investment capital costs $(€)$,

$E_{annually}$ – annually produced energy (kWh),

c_{elec} – approximated price of electricity during that period $(€/\mathrm{kWh})$,

TAC – total annualized costs $(€)$,

t – operational lifetime of the project (years).

2.5.3 Local economic impact

Even though majority of economic assessment is from the point of view from the company, local economic impact is the external impact assessment of the renewable energy project. Divided into two parts, *Reliability of electricity production* and *Job creation*, offers the missing piece of a holistic economic assessment.

Reliability of electricity production is measured in percentage – time per year that an energy system is actively providing electricity to the grid. The reliability of electricity production is a critical parameter for maintaining grid stability and ensuring a consistent power supply to meet demand. For example, hydroelectric power can continuously provide electricity, whereas solar and wind power are reliant on sun and wind. Due to unpredictable weather patterns, day-night cycle and other factors, solar and wind power cannot constantly supply the grid with power. Hence renewable investments should be analysed for their ability to provide.

One way is to quantify this metric is by comparing the annually produced energy to the theoretical maximum based on the deployed capacity. This method calculates the systems efficiency based on the energy losses due to weather conditions or DC to AC electricity transformation.

Whereas a more generalized but less precise method is to use existing research on renewable energy technologies' production patterns. By using the values from the following table, it is a safe approximation of the reliability of energy production.

TABLE 1. Renewable energy production %time per day, year – assumed average due to varying geographical weather patterns (IEA 2022).

Technology	Photovoltaic solar	Offshore wind	Onshore wind	Hydropower
Active production %time per day, yr	35-45%	75-85%	70-85%	100%

When it comes to approximating the created jobs of an investment of potential energy projects is not as straightforward due to varying scales, industries, and technologies. To simplify and generalize this step, an industry average can be taken to calculate the estimate jobs created in a potential energy investment.

$$Jobs\ created = E \cdot \tau \ , \tag{9}$$

where:

E – installed capacity of the project (MW),

τ – technology-based coefficient "jobs per MW" deployed.

In 2019, Aldieri, L. et al. performed a thorough literature review on studies that assessed created jobs in wind power investments. Even though research papers differed in labour markets and labour intensity of the country – they concluded that on average 5.7 jobs are created per MW deployed wind power. (Aldieri et al. 2019). Another research on renewable energy's impact on jobs, calculated that 4 jobs are created per MW deployed solar power (Kim & Mohommad 2022).

2.6 Social Impact Assessment

Considered to be one of the main goals of modern project development, social welfare is gaining more priority in decision making. Measuring the social impacts of an energy project is vital for its long-term success. It helps understand how the project affects local communities, public health, employment, and overall quality of life. Social impact aligns with principles of corporate social responsibility, making it a pivotal indicator in the project’s overall viability.

2.6.1 Labour conditions

Assessing the labour conditions of a project is a study on its own. The analysed literature offers various approaches, but most accurate and industry-preferred method is a Social Life Cycle Assessment (SLCA). Like Environmental LCA, it takes into consideration all stages within the LCA boundary, compiling impacts and interpreting results for a conclusive assessment.

Written for the European Commission in 2015, Sala, Vasta, Mancini, Dewulf & Rosenbaum offered a complete systematic documentation for performing a SLCA. The approach is a state-of-the-art systematic LCA that focuses solely on assessing the social impacts. This paper is the recommended reference for a complete SLCA. The goal and scope, life cycle inventory should align with Environmental LCA to maintain consistency. Assessing *Labour conditions* is done by evaluating the compliance with international laws and standards, including working hours, child labour, poverty, wages, safety, and others. The S-LCA approach uses these various indicators to describe the compliance with a specific performance reference point. For example, the European Convention on Human Rights or International Labour Organization. (Sala et al. 2015).

The quantitative assessment is assigning a quantitative value to each project based on compliance with European Convention on Human Rights (ECHR). An evaluation of a project's compliance with the ECHR is rated on a scale of 1 to 5 is interpreted as follows:

(1) **Exemplary Compliance:** The project fully aligns with all aspects of the ECHR, actively promoting fair labour practices, workers' rights, and creating a positive and supportive work environment.
(2) **Strong Compliance:** While not perfect, the project demonstrates strong adherence to the principles of ECHR, with minor areas for improvement. It has key labour standards and worker protections effectively.

(3) **Moderate Compliance:** The project displays moderate compliance, meeting some criteria outlined in the convention but requiring notable improvements in certain aspects to fully align with human rights standards.

(4) **Limited Compliance:** The project shows limited compliance with the European Convention on Human Rights, indicating significant shortcomings that need urgent attention and corrective measures.

(5) **Non-Compliance:** The project lacks compliance with the fundamental principles of the ECHR, necessitating immediate action to address severe deficiencies and ensure conformity with human rights standards.

2.6.2 Human health impact

Human toxicity potential considers the toxicity of emitted substances and their potential harm to human populations, measured as the same impact of 1,4 dichlorobenzene (g1,4-DBeq/kWh). The method for quantifying this impact criterion is the same as for all other LCA-based criteria. Not only is this well-established approach, but also additional consistency is created by applying the same LCA method for multiple assessment criteria. Because LCA process flow is created once (e.g. wind turbine), then the life cycle inventory and process flows will remain the same for multiple impact assessments.

2.6.3 Public acceptability

Public perception and acceptability of an energy project is key to its initial accept and long-term support. Since the public has the power to adjust or even revoke proposed energy projects, it is crucial to assess the support of the public for the long-term success of an investment.

Although generally supported by the population, renewable energy projects are having lower support among locals. This phenomenon is called the “Not in My Back Yard” syndrome when local residents oppose the development of renewable energy projects. Even though some locals prefer the visuals of wind turbines on the horizon, some see them as intruding and even damaging to quality of life. (Britannica 2023).

Assessing the public support of an energy project should focus directly on locals, hence the generally used method in quantifying public support is a public survey. The result of the survey is the percentile (%) of respondents that are in support of a project's development. For example, a public survey in 2023 by Enefit Green inquired "Do you support the development of new offshore wind farms?" Possible answers ranged from 1 to 5. Respondents answering 1 or 2 are classified as being "against"; and respondents answering 4 or 5 are classified "in support". Percentile in support of a project is calculated by the following formula:

$$Public\ support\ (\%) = \frac{R_{support}}{R_{total}}\ , \qquad (10)$$

where:

$R_{support}$ – respondents in support (answering "4" and "5"),

R_{total} – total number of respondents.

3 MULTI-CRITERIA DECISION ANALYSIS (MCDA)

To compare energy investment scenarios, the results of the assessments should be combined in a single score value – sustainability index. It is a challenging mathematical problem: compiling every impact criterion into a single index of sustainability, as units of impact values are completely different.

MCDA methods combine multiple criteria in a structured way, in result providing a single-score value. In 2017 Mardani et al. conducted a review of most used MCDA methods in energy management problem-solving. Most popular methods included: Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and hybrid MCDA methods. While TOPSIS, ANP, PROMETHEE was used in 5% of energy management decisions - AHP was used in 25% of the studies. (Mardani et al. 2017).

3.1 Analytic Hierarchy Process (AHP)

Developed by R. W. Saaty in 1980s, AHP integrates multiple criteria into a single value used to compare alternative scenarios. The criteria are normalized and weighted for a single value index in result, enables the integration of different criteria even if the units are different. AHP works based on a pairwise comparison of criteria relative importance – subjective judgement of which criteria are more important than others. (Saaty 1987).

The simplicity of AHP makes it widely used in cases, where decisions must be taken with data-based arguments and without human intuition. The method is meant for case-specific comparison analysis - perfect for this SA framework. Since there are nine different SA impact criteria in this framework, AHP would provide the mathematical solution in integrating the criteria into a single sustainability index.

3.2 Normalization and weighing

First steps of the analytical hierarchy process are as follows:

1. the creation of hierarchy with a Goal at the top,
2. list of alternatives among which the best alternative must be found,
3. list the criteria which must be considered with respect to the main Goal,
4. list of sub-criteria, if necessary, for a more thorough analysis.

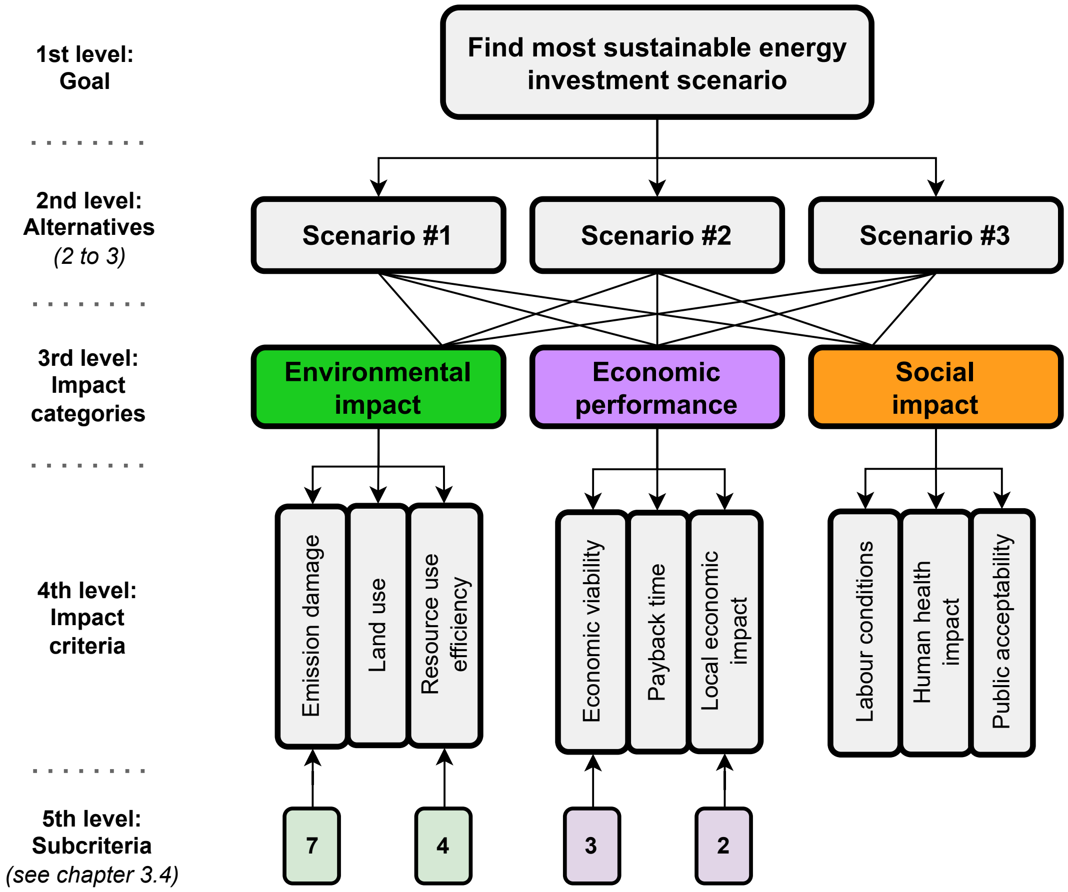


FIGURE 6. AHP structure for this sustainability assessment framework.

Having specified a main goal of “finding the most sustainable energy project scenario,” all following steps and decisions must align with the goal. Impact categories are based on the three pillars of sustainability whereas impact criteria selection comprises of 21 total criteria, see Chapter 2.4.

The next step of AHP is the pairwise comparison matrix. It is created by judging all criteria in pairs for their relative importance. Pairwise judgments are done by inputting numeric value from “relative importance” table below:

TABLE 2. The relative importance scale (Saaty 1987).

Value	Definition
1	Equally important
3	Moderately more important
5	Strongly more important
7	Significantly more important
9	Extremely more important
2,4,6,8	Intermediate values between two adjacent importance levels
$\frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \dots, \frac{1}{9}$	Increasingly less important, the inverse value of the corresponding pair

This pairwise comparison is done on each pair of the criteria array, resulting into a matrix. For *n* criteria, the matrix would be a *nxn* cells large. Diagonal equals to 1, as that is the ratio when a criterion is compared to itself (Saaty 1987):

$$M_{n,n} = \begin{bmatrix} C_1/C_1 & C_1/C_2 & \cdots & C_1/C_n \\ C_2/C_1 & C_2/C_2 & \cdots & C_2/C_n \\ \vdots & \vdots & \ddots & \vdots \\ C_n/C_1 & C_n/C_2 & \cdots & C_n/C_n \end{bmatrix} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix}, \qquad (11)$$

where:

$M_{n,n}$ – n by n matrix,

C_1 – criterion 1,

C_2 – criterion 2,

a_{12} – relative importance value of criterion 1 to criterion 2.

Since there are 9 criteria in this SA framework, then it would create a 9x9 array (see Table 4). For example, if from the company’s perspective:

- *Emission damage* is significantly more important than *Land use* = 7,
- *Emission damage* is just as important as *Economic feasibility* = 1,
- *Land use* is significantly less important than *Economic feasibility* = $\frac{1}{7}$.

Fortunately, only half of the criteria pairs need to be manually compared for their importance, as the bottom triangular matrix it is just the inverse of the corresponding cell above the diagonal. If a_{ij} is the relative importance of criterion *i* and criterion *j* of the matrix, then the corresponding value of the lower diagonal is calculated by (Youssef, L. 2019):

$$a_{ji} = \frac{1}{a_{ij}} \ , \tag{12}$$

where:

a_{ji} – the inverse of a_{ij}.

Next step of AHP is to calculate the normalized weights of criteria (see Table 6). This is integration of all relative importance values into a proportional weight of each criterion. First, summation of the criterion’s relative importance by columns, then creating a normalized matrix using the following equation (Saaty 1987):

$$X_{ij} = \frac{C_{ij}}{\sum C_i} \ , \tag{13}$$

where:

i – criterion i on vertical axis,

j – criterion j on horizontal axis,

X_{ij} – normalized weight of a criteria pair,

C_{ij} – criteria relative importance value,

$\sum C_i$ – sum of relative importance values in column criterion i.

Finally, developing the priority vector average in each row of the normalized matrix (Table 6). The row averages form the priority vector, which is the proportional weight of each criterion in relation to others (Saaty 1987):

$$W_j = \frac{\sum X_{ij}}{n} \ , \tag{14}$$

where:

W_j – normalized weight of criterion j,

$\sum X_{ij}$ – normalized matrix row sum,

n – number of criteria.

3.3 Degree of consistency

Before calculating the final product of impact values with its respective weight, certain inconsistencies should be taken into consideration. Simply put, if criterion relative importance A > B, and criterion B > C, then criterion A should be proportionally larger than C. Considering the risk of human error, the following procedure is a crucial step in a consistent AHP.

The degree of consistency exposes how consistent were the importance value inputs according to the simple explanation. Firstly, analysing the normalized weight sum of criteria by the following matrix multiplication (Youssef 2019):

$$Weighted\ sum_{n,n} = \begin{bmatrix} C_1/C_1 & C_1/C_2 & \cdots & C_1/C_n \\ C_2/C_1 & C_2/C_2 & \cdots & C_2/C_n \\ \vdots & \vdots & \ddots & \vdots \\ C_n/C_1 & C_n/C_2 & \cdots & C_n/C_n \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix} = \begin{bmatrix} \Upsilon_1 \\ \Upsilon_2 \\ \vdots \\ \Upsilon_n \end{bmatrix}, \qquad (15)$$

where:
first matrix - initial relative importance table,
second matrix - normalized weight of criteria (result of Equation 14.),
Υ_n – weighted sum of criterion n.

Following this, the Principal Eigen value is obtained from the weighted sum of each criterion (Υ_n), and the sum of relative importance column criterion ($\sum C_n$).

The resulting Υ_n array is then compared to the normalized weight of the respective criterion. Principal Eigens max value (λ_{max}) is the average of ratio $\frac{\Upsilon_i}{W_i}$ of each criterion. (Youssef 2019):

$$\lambda_{max} = \frac{\sum_{i=1}^{n} \frac{\Upsilon_i}{W_i}}{n}, \qquad (16)$$

where:

Υ_i – weighted sum of criterion *i*,

W_i – normalized weight of criterion *i*.

Then $\lambda_{max}$is the average of this $Ratio_i$ for each criterion. Lastly the consistency ratio (C.R.) is obtained by comparing the consistency index (C.I.) with the random consistency index (R.I.), which is a calculated number for *n* criteria in AHP study. The consistency ratio is satisfactory if CR ≤ 0.10. However, if CR > 0.10, there are inconsistencies in relative importance values manual input, and they should be revaluated until CR is less or equal to 0.10 (Saaty 1987).

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{17}$$

$$CR = \frac{CI}{RI} \tag{18}$$

TABLE 3. Consistency Index per used criteria count *n* (Saaty 1987).

n	1	2	3	4	5	6	7	8	9	10
Random Consistency Index (R.I.)	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

3.4 Sub-criteria impact value product

The last step of AHP would be to create *n* matrixes by manually comparing all alternatives with one and other in respect to each of the criterion. Fortunately, it can be done automatically by exchanging the manual work with ratios of impact values for each scenario.

Since impact values of LCA, Financial analysis, and public surveys are raw input data, it is possible to take the ratios of each scenario per criterion (see Table 10). By interchanging the impact value ratios per scenario, this is used as manual input but completely accurate and based on impact data values.

$$Ratio_i = \frac{\mathrm{scenario1}_i}{scenatio2_i}\ , \tag{19}$$

where:

$Ratio_i$ – ratio between scenarios',
$\mathrm{scenario1}_i$ – scenario 1 impact value in criterion *i*,
$\mathrm{scenario2}_i$ – scenario 2 impact value in criterion *i*.

Finally, the ratios are multiplied with the normalized weight of the respective criteria and averaged for scenarios' total Sustainability Index. Tables 11 – 13.

$$Normalized\ weight_i = Ratio_i \cdot W_i \tag{20}$$

$$\boldsymbol{SI} = \frac{\sum_{i=1}^{n} weight_i}{n} \tag{21}$$

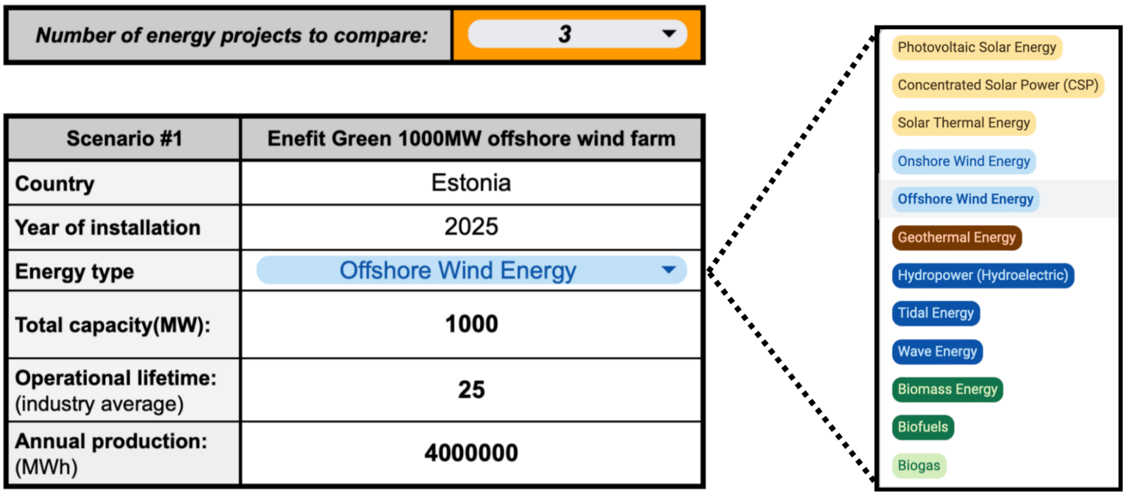
where:

$Ratio_i$ – ratio between scenarios' impact values of criteria,
W_i – normalized weight of criterion j,
$\boldsymbol{SI}$ – final sustainability index of the scenario,
n – number of criteria.

Once Sustainability Index has been calculated, it is converted into 0-1 scale in terms of relative value to other alternative scenarios. This enables a comprehensive way to conclude which alternative is the most sustainable.

4 TOOL DEVELOPMENT

The SA framework was made created into a practical tool using Google Sheets. First step is the definitions of comparable energy investment scenarios:



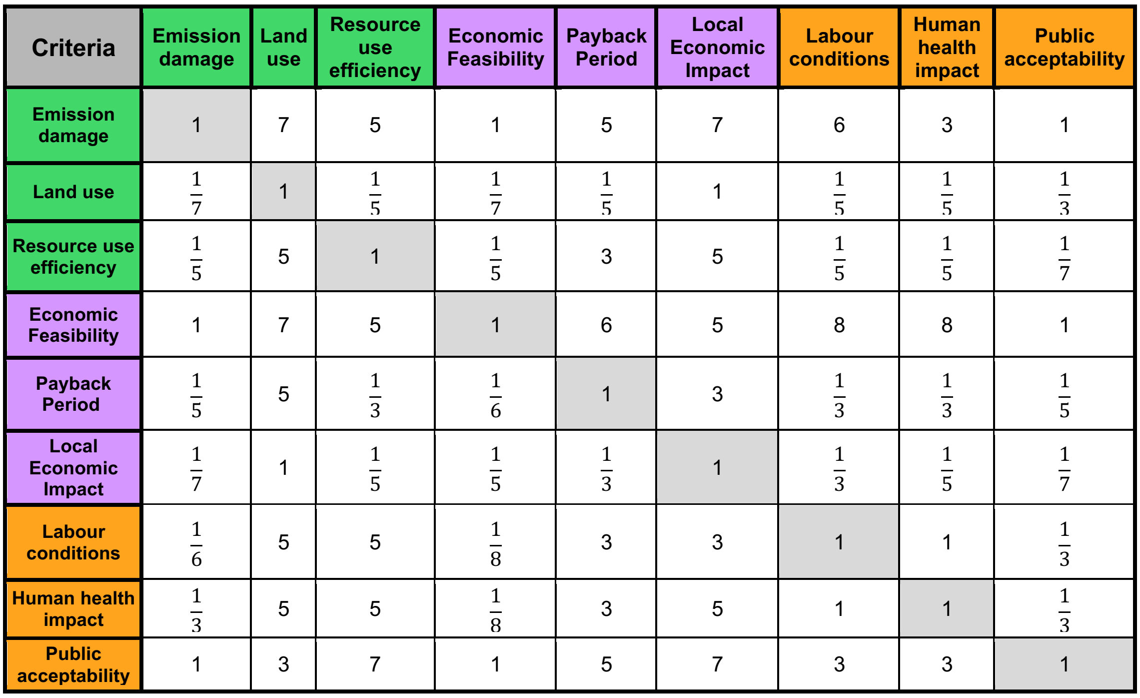
Number of energy projects to compare:	3

Scenario #1	Enefit Green 1000MW offshore wind farm
Country	Estonia
Year of installation	2025
Energy type	Offshore Wind Energy
Total capacity(MW):	1000
Operational lifetime: (industry average)	25
Annual production: (MWh)	4000000

FIGURE 7. Defining renewable energy investment scenarios.

In the next step it is recommended that analysts work together with the company to accurately determine which criteria are more important in their respective situation. As AHP is meant for case-specific assessments, this step is crucial.

TABLE 4. Relative importance matrix – input.



Criteria	Emission damage	Land use	Resource use efficiency	Economic Feasibility	Payback Period	Local Economic Impact	Labour conditions	Human health impact	Public acceptability
Emission damage	1	7	5	1	5	7	6	3	1
Land use	$\frac{1}{7}$	1	$\frac{1}{5}$	$\frac{1}{7}$	$\frac{1}{5}$	1	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{3}$
Resource use efficiency	$\frac{1}{5}$	5	1	$\frac{1}{5}$	3	5	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{7}$
Economic Feasibility	1	7	5	1	6	5	8	8	1
Payback Period	$\frac{1}{5}$	5	$\frac{1}{3}$	$\frac{1}{6}$	1	3	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{5}$
Local Economic Impact	$\frac{1}{7}$	1	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{3}$	1	$\frac{1}{3}$	$\frac{1}{5}$	$\frac{1}{7}$
Labour conditions	$\frac{1}{6}$	5	5	$\frac{1}{8}$	3	3	1	1	$\frac{1}{3}$
Human health impact	$\frac{1}{3}$	5	5	$\frac{1}{8}$	3	5	1	1	$\frac{1}{3}$
Public acceptability	1	3	7	1	5	7	3	3	1

Next is the input of all data from Environmental LCA, energy calculations, financial viability assessment, S-LCA, and local questionnaires.

TABLE 5. Impact criteria value input (values based on Chapter 5).

		Impact critera	Impact value	Unit (per kWh)
Environmental Assessment	Emission damage	Global Warming Potential	3.6	gCO2-equivalent
		Photochemical Oxidant Creation	0.94	mgC2H4-eq
		Accidification potential	9.7	mgSO2-eq
		Eutrophication potential	0.9	mgPO4-eq
		Terrestrial ecotoxicity	7.8	mg1,4-DB-eq
		Freshwater ecotoxicity	13.3	mg1,4-DB-eq
		Marine ecotoxicity	0.35	g1,4-DB-eq
		Land use (Direct)	139	km2
	Resource use efficiency	Abiotic resource depletion	0.03	MJ
		Water consumption	9.5	g
		Energy consumption	1833	GWh
		Energy Payback time	6.1	months
Economic Assessment	Economic viability	Capital costs	€3,907,000	cost per deployed MW
		Total annualized costs	€60,970	annual cost per MW
		Levellized Cost of Electricity	€0.051	per kWh
		Investment Payback period	12.3	years
	Local impact	Reliability of energy production	80%	operational time per year
		Job creation	5700	total jobs
Social assessment		Labour conditions	4	Compliance with ECHR (1 to 5)
		Human toxicity	1.7	g1,4-DB-eq per kWh
		Public acceptability	69%	Locals in support

An improvement of AHP is the harmonization impact criteria. Since the goal is to find which scenario has the highest sustainability index, the tool needs to calculate for the highest number. Some criteria impact this index positively, however, others negatively. For example, *Global Warming Potential (GWP)* - the higher the potential impact, the less sustainable the energy project should be. Hence the impact value should be inversed $(\frac{1}{GWP})$ – harmonized for the Sustainability Index. The same goes for all other criteria except for, Local Economic Impact and Public acceptability: the higher the value, the more sustainable they are, the better for scenario's Sustainability Index. The tool does this automatically.

Following is the normalization of all criteria, see Eq13 & Eq14 for the formula. The final normalized weight of a criteria is the average of the corresponding row.

TABLE 6. Normalized matrix - priority vector (weight of each criterion).

Criteria	Emission damage	Land use	Resource use efficiency	Economic Feasibility	Payback Period	Local Economic Impact	Labour conditions	Human health impact	Public acceptability	Normalized weight
Emission damage	0.239	0.179	0.174	0.253	0.188	0.189	0.299	0.177	0.223	**0.214**
Land use	0.034	0.026	0.007	0.036	0.008	0.027	0.010	0.012	0.074	**0.026**
Resource use efficiency	0.048	0.128	0.035	0.051	0.113	0.135	0.010	0.012	0.032	**0.063**
Economic Feasibility	0.239	0.179	0.174	0.253	0.226	0.135	0.399	0.472	0.223	**0.256**
Payback Period	0.048	0.128	0.012	0.042	0.038	0.081	0.017	0.020	0.045	**0.048**
Local Economic Impact	0.034	0.026	0.007	0.051	0.013	0.027	0.017	0.012	0.032	**0.024**
Labour conditions	0.040	0.128	0.174	0.032	0.113	0.081	0.050	0.059	0.074	**0.083**
Human health impact	0.080	0.128	0.174	0.032	0.113	0.135	0.050	0.059	0.074	**0.094**
Public acceptability	0.239	0.077	0.244	0.253	0.188	0.189	0.150	0.177	0.223	**0.193**
sum	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	

To see how consistent the weights are, Degree of Consistency is calculated (Eq15). The inconsistencies originate from the input relative importance values.

TABLE 7. Degree of consistency.

Criteria	Normalized weight (W)	Weighted sum (Υ)	Ratio ($\frac{W}{\Upsilon}$)	λ_{max}	Consistency Index (CI)	Random Index (RI)	Degree of consistency	Consistency check tool ON/OFF
Emission damage	0.214	2.346	10.989	10.515	**0.18940**	**1.45**	**0.13**	**[x]**
Land use	0.026	0.239	9.213					
Resource use efficiency	0.063	0.613	9.795					
Economic Feasibility	0.256	2.982	11.667					
Payback Period	0.048	0.454	9.510					
Local Economic Impact	0.024	0.234	9.712					
Labour conditions	0.083	0.967	11.592					
Health impact	0.094	1.051	11.197					
Public acceptability	0.193	2.117	10.957					
sum	**1.000**	**11.004**						

Degree of consistency is satisfactory if ***CI / RI <0.10***

Turn ***ON*** *tool to see inconsistencies in TABLE 6. It is then recommended to* ***reevaluate*** *the* ***relative importance values for highlighted cells.***

Cause for the inconsistency

If criteria ***A > B*** *&* ***B > C****, then* ***A >> C*** *In Table 1. difference between* ***A and C*** *should be bigger than importance difference* ***A to B*** *and* ***B to C****.*

There is an additional tool that has been implemented. **Consistency check tool** is meant to help the debugging process of human error in relative importance matrix (Eq11). When turned “ON”, cells that create an error are highlighted in the table. The mathematical process is as follows:

First, each criterion’s importance is ranked from 1 to 9 (from Table 6.) per each row, that is, in respect to criterion on row *n*. Then the average rank of each criterion by columns is calculated:

TABLE 8. Importance ranking order for consistency debugging tool.

	Importance ranking order per row *(in respect to the criterion on row n)*	**Emission damage**	**Land use**	**Resource use efficiency**	**Economic Feasibility**	**Payback period**	**Local Economic Impact**	**Labour conditions**	**Human health impact**	**Public acceptability**
row 1	**Emission damage**	3	7	9	2	6	5	1	8	4
row 2	**Land use**	3	5	9	2	8	4	7	6	1
row 3	**Resource use efficiency**	5	2	6	4	3	1	9	8	7
row 4	**Economic Feasibility**	4	7	8	3	5	9	2	1	6
row 5	**Investment Payback Period**	3	1	9	5	6	2	8	7	4
row 6	**Local Economic Impact**	2	5	9	1	7	4	6	8	3
row 7	**Labour conditions**	8	2	1	9	3	4	7	6	5
row 8	**Human health impact**	5	3	1	9	4	2	8	7	6
row 9	**Public acceptability**	3	9	2	1	6	5	8	7	4
	Avgerage rank	**4.000**	**4.556**	**6.000**	**4.000**	**5.333**	**4.000**	**6.222**	**6.444**	**4.444**

Based on these ranking results, there is conditional formatting algorithm on all individual Table 4 cells, where a cell will be highlighted in red if:

1. the cell in question is above the diagonal – to only check cells where input was done manually,
2. importance rank of criteria *i* is |less or more| than 3.5 as compared to its average rank per column.

$$\begin{gathered} = \text{if} \; (\; \text{AND} \; (\\ (row_{ij} - column_{ij}) < 1, \\ |cell_i - avgRank_i| > 3.5 \;) \; , \\ \text{TRUE} \; , \text{FALSE} \;) \end{gathered} \tag{22}$$

After achieving Degree of Consistency less or equal to 0.10, the weight of criteria is consistent enough for use. Next step is the impact value product of all sub-criteria. For example, Economic viability is comprised of three sub-criteria: Capital cost, Total annualized costs, LCOE. The cells for Capital cost are the respective ratio of $(\frac{scenario_i}{scenario_j})$. This is done on every sub-criterion on every scenario ratio. Finally, the row is averaged for scenario's impact value of Economic viability.

TABLE 9. Combined sub-criteria into a single value for respective criteria.

Economic viability	Capital costs	Scenario #1	Scenario #2	Scenario #3	Total annualized costs	Scenario #1	Scenario #2	Scenario #3	Levellized Cost of Electricity	Scenario #1	Scenario #2	Scenario #3	Average (economic viability per scenario)
	Scenario #1	1	0.416	0.230	Scenario #1	1	0.537	0.115	Scenario #1	1	0.529	0.745	**0.619**
	Scenario #2	2.403	1	0.554	Scenario #2	1.861	1	0.214	Scenario #2	1.889	1	1.407	**1.259**
	Scenario #3	4.341	1.807	1	Scenario #3	8.701	4.675	1	Scenario #3	1.342	0.711	1	**2.731**

This step is repeated on all 9 impact criteria - full table of all criteria and their respective sub-criteria ratio analysis can be seen in Appendix 1.

TABLE 10. Scenarios' impact values after combining every sub-criteria.

Criteria	Emission damage	Land use	Resource use efficiency	Economic Feasibility	Payback period	Local Economic Impact	Labour conditions	Human health impact	Public acceptability
Scenario #1	4.391	0.468	2.402	0.619	0.753	5.750	1.083	3.647	1.095
Scenario #2	1.883	1.275	1.083	1.259	1.655	5.750	1.083	1.127	0.809
Scenario #3	0.505	12.752	3.545	2.731	0.936	0.512	0.867	0.544	1.174

Finally, these scenarios' combined criteria impact values are multiplied by the criteria weights to receive their weighted impact value. The final Sustainability Index is the averaged value of each row.

TABLE 11. Final calculations – Sustainability Index of each scenario.

Criteria	Emission damage	Land use	Resource use efficiency	Economic Feasibility	Payback period	Local economic impact	Labour conditions	Human health impact	Public acceptability	Sustain-ability index
weight (wi)	**0.214**	**0.026**	**0.063**	**0.256**	**0.048**	**0.024**	**0.083**	**0.094**	**0.193**	
Scenario #1	0.938	0.012	0.150	0.158	0.036	0.139	0.090	0.342	0.212	**0.231**
Scenario #2	0.402	0.033	0.068	0.322	0.079	0.139	0.090	0.106	0.156	**0.155**
Scenario #3	0.108	0.331	0.222	0.698	0.045	0.012	0.072	0.051	0.227	**0.196**

Sustainability Index can now be compared to hypothetical energy investment scenarios in assessing which project would be more sustainable in the long-term.

5 CASE STUDY

Eesti Energia is the largest energy solution company in Estonia. With nearly 400MW of wind energy and 30MW of solar farms in operation, it is one of the leaders of renewable energy investments in the Baltics. In July 2023, the sister company Enefit Green revealed plans for an offshore wind farm in the Baltic Sea's Gulf of Riga, with a capacity of 1 gigawatt (1000 MW). It will be the first ever offshore wind farm in the Baltic States, and the largest wind farm in the whole Baltic Sea. It will produce more 4 TWh annually, providing electricity to half of Estonia. (Enefit Green 2023).

This SA framework was created to compare two energy investment scenarios – 1GW The Gulf of Riga offshore wind farm and a similar capacity 1GW onshore wind farm. For further development of the tool, a third project is included: 50 MW photovoltaic solar farm. This decision enables the comparison between different energy systems, and different total capacities. The results of the study will provide Enefit Green quantitative feedback for the overall sustainability of the Gulf of Riga 1GW offshore wind farm project.

5.1 Environmental assessment

Life Cycle Impact Assessment (LCIA) is the method used to calculate three impact criteria: *Emission damage*, *Resource use efficiency*, *Human health impact (health and safety)*. Based on industry averages, it is assumed that the wind projects' operational lifetime is 25 years, and PV solar system: 25 years (Sustainable Features 2019). The scope of LCIA includes:

1. Environmental impacts from raw material extraction and processing.
2. Impacts from manufacturing process of the wind turbines and solar panels.
3. Transportation of parts to the deployment site.
4. Construction of the wind farm and deployment of solar panels.
5. ~~End-Of-Life~~: recycling is not considered within the LCA boundaries.

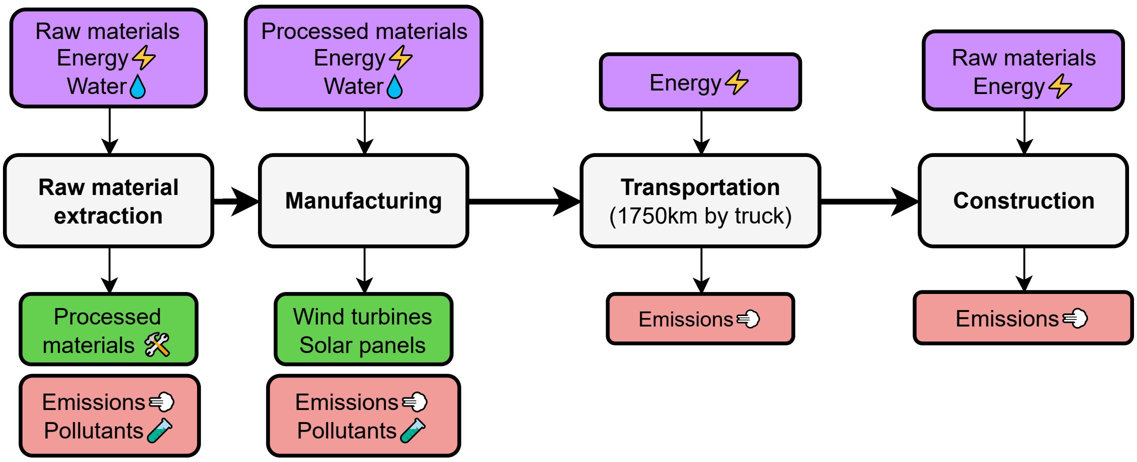


FIGURE 8. Life cycle map of LCIA – wind turbines & solar panels.

It is assumed that raw material extraction, processing, takes place in Germany. Transportation of wind turbine parts and panels from Hamburg to Tallinn by flatbed trucks: 1750km long distance, while consuming 30L/100km diesel with maximum capacity of 30 tons (FluentCargo 2023). Additionally, concrete is not transported from Germany, as it is sourced locally in Estonia.

According to Enefit Green (2023), industry leading 15MW wind turbines will be deployed in the offshore windfarm. In the two hypothetical scenarios, 500W monocrystalline silicon PV panels and 4.2MW onshore wind turbines are used.

The functional unit is the reference value used to measure the environmental performance of the technology. In this case, the unit is 1kWh. This means that total impacts are averaged over the technology's entire lifetime energy production in kilowatt-hours (kWh).

OpenLCA software is used for building the material flow and process simulation for each project scenario. LCIA method of choice is the ReCiPe2016. Impact assessment scope is 100-years, which means the calculation considers the effects of the emissions and substances over a century.

When assessing the impact of manufacturing, the initial step involves calculating the weight of raw materials. First, total weight of energy projects is calculated (Table 12). Then, material weight percentages from other studies are used to estimate the mass of raw materials used in projects (Tables 13 & 14).

TABLE 13. Total weight of energy projects.

Scenario	Offshore 1GW wind farm	Onshore 1GW wind farm	Photovoltaic 50MW solar farm
1 unit output (MW)	15 *1	4.2 *3	5 x10^{-6}
Units (turbines/panels)	67 *1	238	100 000
Unit weight (kg)	875 000 *2	396 000 *3	32 *4
Total weight (kg)	**58.6 x10^{6}**	**131.9 x10^{6}**	**3.2 x10^{6}**
Weight (kg) **per** W	58.6	131.9	64.0

*1 – (Eesti Energia 2023)
*2 – (National Renewable Energy Laboratory 2020)
*3 – (EWEA n.a.)
*4 – (University of Technology Sydney 2019)

The total weight is multiplied by the material's respective weight percentage. A study of solar panel material composition by University of Technology Sydney (UTS) is used. The same approach is repeated for offshore and onshore wind turbines, based on a wind turbine LCA study performed by Bonou, Laurent & Olsen (2016):

TABLE 14. Approximate mass of raw materials in respective wind turbines.

Material	Weight (%) in offshore wind turbine *1	Weight (%) in onshore wind turbine *1	Total mass (kg) in offshore 1GW wind farm	Total mass (kg) in onshore 1GW wind farm
Steel	73%	20.5%	4.28 x10^{7}	2.70 x10^{7}
Concrete	4.7%	72.8%	2.75 x10^{6}	9.60 x10^{7}
Iron	6.4%	1.8%	3.75 x10^{6}	2.37 x10^{6}
Plastics	3.6%	1.2%	2.11 x10^{6}	1.58 x10^{6}
Epoxy	2.4%	1%	1.41 x10^{6}	1.32 x10^{6}
Glass fibre	2.3%	0.8%	1.35 x10^{6}	1.06 x10^{6}
Aluminium	2%	0.7%	1.17 x10^{6}	9.23 x10^{5}
Copper	1.4%	0.7%	8.20 x10^{5}	9.23 x10^{5}
Lead	1%	0.4%	5.86 x10^{5}	5.28 x10^{5}

*1 – (Bonou, Laurent & Olsen 2016)

TABLE 15. Approximate mass of raw materials in solar panels.

	Glass	Plastics	Aluminium	Silicon	Copper	Other
Weight (%) *1	76%	10%	8%	5%	1%	<0.1%
1 panel	23.32	3.2	2.56	1.6	0.32	0.032
50MW system	2.3 x10^6	3.2 x10^5	2.6 x10^5	1.6 x10^5	3.2 x10^4	3.2 x10^3

*1 – (UTS 2019)

Finally, the total impact assessment results are calculated. Since it is a comparison of scenarios, the used units can be altered as long they remain constant between scenarios. Impacts are averaged per produced kWh over the entire operational lifetime. This is the approach used in other studies – find which is more efficient for the life cycle sustainability efficiency. For total LCIA case-by-case analysis see Appendix 2.

TABLE 16. LCIA results per kWh – averaged per the total produced energy over the entire operational lifetime.

Impact category	1GW offshore wind farm	1GW onshore wind farm	50MW PV solar farm
Global warming potential (g CO_2eq /kWh)	3.6	6.8	73.2
Abiotic resource depletion (MJ /kWh)	0.03	0.08	0.17
Photochemical Oxidant Creation Potential (mg C_2H_4eq /kWh)	0.94	2.38	4.65
Acidification potential (mg SO_2eq /kWh)	9.7	23.1	47.1
Eutrophication potential (mg PO_4eq /kWh)	0.9	2.3	3.4
Terrestrial ecotoxicity (mg 1,4-DBeq /kWh)	7.8	20.9	49.8
Freshwater ecotoxicity (mg 1,4-DBeq /kWh)	13.3	30.7	212.8
Marine ecotoxicity (g 1,4-DBeq /kWh)	0.35	1.0	4.1
Human toxicity potential (g 1,4-DBeq /kWh)	1.7	5.5	11.4
Water consumption (g /kWh)	9.5	26.6	54.6
Total energy consumption (GWh)	2033	2962	122.6

Energy consumption during transportation must be manually calculated due case-specific data, which is not accounted for in OpenLCA ReCiPe model.

$$E_{transport} = \frac{m}{PL_{max}} \cdot S \cdot \eta \cdot \varepsilon \,, \tag{23}$$

where:

$E_{transport}$ – energy used in transportation in MJ,

m – total mass of the project (without concrete) in tons,

PL_{max} – payload of a flatbed truck: *30tons*,

S – distance from Hamburg to the site in Estonia: *1750km*,

η – motor efficiency of the truck: *30L / 100km*,

ε – energy density of diesel: *38MJ / L diesel* (DPI, 2016).

By using Eq1., direct land use of three scenarios is calculated:

- 1GW offshore wind farm: $1000 \cdot 0.139\ \mathrm{km^2/MW} = 139\ \mathrm{km^2}$
- 1GW onshore wind farm: $1000 \cdot 0.051\ \mathrm{km^2/MW} = 51\ \mathrm{km^2}$
- 50MW PV solar farm: $50 \cdot 0.102\ \mathrm{km^2/MW} = 5.1\ \mathrm{km^2}$

Enefit Green claims that the Gulf of Riga offshore wind farm will generate 4TWh per year (Enefit Green 2023). According to Puhkim OÜ calculations (2016), average wind speed in the Gulf of Riga is 9.1 m/s, however, on land in Western Estonia: 7.7 m/s, which is 15% less than that of the sea. That would limit the same 1GW onshore wind farm in generating only 3.4TWh annually.

Lastly, one kW of deployed PV solar farm in Estonia would generate 1022 kWh of electricity annually. That accounts for solar irradiation in Northern Europe (1000 kW/m^2), weather patterns (102 – 127 rainy days per year), monocrystalline solar panel efficiency (20%), and DC to AC inverter efficiency (80%). (SolarGIS 2016). Hence, a 50MW solar farm would produce 51.1GWh each year.

By using Equation X., it is possible to calculate the Energy Payback Time:

- 1GW offshore wind farm: $\frac{E_{consumed}}{AE} = \frac{2033GWh}{4000\ GWh} = 0.508\ yr = 6.1\ (months)$
- 1GW onshore wind farm: $\frac{2962\ GWh}{3400\ GWh} = 0.871\ yr = 10.4\ (months)$

- 50MW PV solar farm: $\frac{122.6\ GWh}{51.1\ GWh} = 2.4\ yr = 28.8\ (months)$

5.2 Economic assessment

To approximate the capital costs of energy projects, average values have been taken form a global report by International Renewable Energy Agency (IREA, 2023) on a per-deployed-kW basis. All data is up to date with renewable energy projects based in Europe, see Table 17.

TABLE 17. Lifetime production of energy

Scenario	Yearly production (GWh)	Operational lifetime (years)	Approx. lifetime production (kWh)
Offshore 1GW wind farm	4 000 000 [*1]	25 [*2]	**1.0 x10^{11}**
Onshore 1GW wind farm	3 400 000	25 [*2]	**8.5 x10^{10}**
Photovoltaic 50MW solar farm	51 100 [*3]	25 [*2]	**1.3 x10^{9}**

*1 – (Eesti Energia 2023)
*2 – (IEA 2022)
*3 – (SolarGIS 2016)

TABLE 18. Financial viability assessment of energy investment scenarios.

		(IREA, 2023)	(Statista, 2023)		
Installation (capital) costs		**Europe: $/kW**	**€/kW**	**per MW**	**TOTAL**
	1GW offshore	€3,907	€3,555	€3,555,370	**€3,555,370,000**
	1GW onshore	€1,626	€1,480	€1,479,660	**€1,479,660,000**
	50MW solar	€900	€819	€819,000	**€40,950,000**
Annualized costs		**Europe: $/kW/yr**	**€/kW/yr**	**Annualized costs**	
	1GW offshore	€67	€60.97	**€60,970,000**	
	1GW onshore	€36	€32.76	**€32,760,000**	
	50MW solar	€8	€7.01	**€350,350**	
Levellized Cost of Electricity		**total expenses**	**per MW**	**Per kWh produced**	
	1GW offshore	€5,079,620,000	€5,079,620	**€0.051**	
	1GW onshore	€2,298,660,000	€2,298,660	**€0.027**	
	50MW solar	€49,708,750	€994,175	**€0.038**	
Investment payback time		**annually produced kWh**	**electricity price (€/kW) *1**	**annual profit (€)**	**Payback time (years)**
	1GW offshore	4.00E+09	€0.0875	€289,030,000	**12.3**
	1GW onshore	3.40E+09		€264,740,000	**5.6**
	50MW solar	5.11E+07		€4,120,900	**9.9**

**1 - average wholesale electricity price Estonia, October 2023*

IEA estimates that wind turbines produce electricity 70-85% of the time throughout the year. It depends on weather patterns, but in the Baltic Sea it is safe to assume that the offshore (and onshore) wind farms will be in operation for 80% of the time. However, solar panels are in operation only when there is sunlight. Estonia, being further north, receives 1753 hours of sunlight per year - of possible 4383h/year. (Climatemps 2014). This means operational percentage of the year of 50MW solar farm is just 40%, which aligns with IEA 2022 report.

Proceeding to created jobs, approximating the jobs in hypothetical scenarios is challenging and unreliable. However, by using Equation 9., job creation estimation is based on industry averages:

- 1GW offshore wind farm: $1000 \cdot 5.7 = 5700\, jobs$,
- 1GW onshore wind farm: $1000 \cdot 5.7 = 5700\, jobs$,
- 50MW solar farm: $50 \cdot 4 = 200\, jobs$.

5.3 Social assessment

1. Labour conditions

Regarding labour conditions of the projects, a thorough Social-LCA would require detailed investigation of raw material extraction sites. Since the energy projects are deployed in Europe, it is assumed that work safety, wages, working hours, and work conditions are up to the highest standards. As defined in the LCA scope, raw materials are extracted and processed in Germany, which is a country well respected in their practices. Hence both wind farm projects are assumed to fully align with all aspects of the European Convention on Human Rights, actively promoting fair labour practices, workers' rights, and creating a positive and supportive work environment. Rating: 5.

The same approach would not work on solar farm, as solar panels have various materials, which are not available in Germany, e.g. Indium and Gallium. By weight they have rather low mass percentage, limiting their impact on Environmental-LCA. However, assessing the social impact of sourcing these materials brings a lot of uncertainty. China, being the largest Indium and Gallium producer, has been notorious for having working conditions. Chinese-owned companies have poor health and safety standards, inadequate ventilation leading to lung diseases, and continuously ignorant local community exploitation. (Guardian 2023). Due to these uncertainties, the rating for solar farm in compliance with the HCHR is 4.

2. Public Acceptability

In October 2023, Enefit Green released the data from an Estonia-wide survey involving approximately 1,100 residents about the development of wind farms near residential areas. The findings indicated that 72% of Estonians support the development of offshore wind farms and 70% support further expansion of on-shore wind energy. However, 63% of locals support the development of an off-shore wind farm near their home and a total of 47% support the construction of an onshore wind farm near their home. (Enefit Green 2023).

To verify and compare these results, an independent public questionnaire was conducted, aimed to analyse public support towards the three scenarios: 1000MW Gulf of Riga offshore wind farm, hypothetical 1000MW onshore wind farm, hypothetical 50MW solar farm.

TABLE 19. Public acceptability survey – %respondents in support.

	1GW offshore wind farm		**1GW onshore wind farm**		**50MW solar farm**	
	General public support	*Local support*	*General public support*	**Local support*	*General public support*	**Local support*
Enefit Green survey	72%	**64%**	70%	**47%**	-	-
Indipendent survey	74%	**69%**	63%	**51%**	79%	**74%**

** Local support for Onshore wind farm and Solar farm was descbribed as: "if you were a local, how much would you support...X project?" This was done to simulate a locals' support for a hypothetical project, and is not a factual result.*

5.4 Results and conclusions

The environmental, economic, and social assessment values are put into the SA framework tool, the values in tables are from this case-study – see Chapter 4.

The MCDA method Analytical Hierarchy Process (AHP) requires a manual prioritization of criteria, which was done from the perspective of Enefit Green. Since the importance values considerably influence the results, it is just a proposed approximation. For example, financial criteria were given slightly more importance than others. See Table 11. for final weights of impact criteria.

To avoid the defects of this subjective approach, an objective calculation is provided in addition to the subjective AHP method. It neglects the importance weighing and just calculates the ratios between scenarios' impact values. Interestingly, the 1GW Gulf of Riga offshore wind farm is the most sustainable of the three scenarios in both subjective weighted and objective unweighted methods.

TABLE 20. Results of the case-study.

	manually weighted (AHP)		*unweighted (based on ratios)*	
	Subjective sustainability index	**Relative sustainability**	**Objective sustainability index**	**Relative sustainability**
1GW the Gulf of Riga wind farm	0.231	**1.000**	0.703	**1.000**
1000MW onshore wind farm	0.155	**0.671**	0.588	**0.836**
50MW photovoltaic solar farm	0.196	**0.850**	0.635	**0.904**

The results strongly support Enefit Green's choice to invest in the 1GW Gulf of Riga offshore wind farm. Both subjective weighted and objective unweighted methods indicate its superior sustainability to the hypothetical scenarios. This conclusion reinforces the long-term sustainability of the Gulf of Riga offshore wind farm investment.

Seeing as 50MW solar farm is more supported by the public and initial investment costs are much lower than that of the wind farms, it is also a recommended to keep investing in solar farms across Estonia. Unfortunately, based on the LCA, solar panels a much higher damage environmental impact in their life cycle per kWh. Due to the rare earth metals required in manufacturing, uncertain labour conditions, and less effective energy use per kWh produced – photovoltaic solar power is generally a less sustainable choice than wind power.

6 DISCUSSION

The presented study offers a systematic tool for sustainable decision-making in the renewable energy sector. As majority of companies focus solely on the economical aspect, the overall sustainability of their energy investments should not be taken for granted. By integrating environmental, economic, and social dimensions, the SA framework tool addresses all three pillars of sustainability, translating them into a single comparable Sustainability Index.

Literature review revealed the necessity for a generalized framework of energy investment comparison, as some were subjectively case-specific, while others lacked a holistic criteria selection. Two SA framework reviews were analysed, and a generalized selection of impact criteria was created. The criteria were selected based on their significance, objectivity, and practicality for the tool. Multi-Criteria Decision Analysis method of choice, AHP, proved to be most applicable in this case due to its adaptability to case-specific scenarios. For the tool's validation, a case-study was conducted to analyse its practical use in a real-world scenario. The results of the case study provided valuable insights into offshore, onshore wind and solar energy project overall sustainability, as well as proving tool's capability to work with various technologies and differing project capacities.

LCA results of the wind power projects are comparably similar to a real wind turbine LCA study by the manufacturer of 4.2MW wind turbines. (Vestas, 2022). *Global Warming Potential* (GWP) for offshore wind: 3.6g, onshore: 6.8g, solar farm: 73.2g per produced kWh over the operational lifetime. Compared to industry averages – offshore wind: 8.1gCO_2eq/kWh, onshore: 7.0gCO_2eq/kWh, solar: 49gCO_2eq/kWh (IEA 2022). It seems that a 15MW offshore wind farm is more efficient than an industry average 5MW turbine. Energy Payback Time (EPBT) for offshore wind turbines was 6.3 months, onshore: 10.4 months, solar: 28.8 months. Industry average show a comparable EBPT of wind turbines: 5-9 months and solar panels: 24 months (IEA 2022). Concluding that solar panels require more raw materials per kWh and are not as efficient at producing energy, hence their GWP and EPBT is considerably higher than that of wind farms.

Financial assessment on the three scenarios proved challenging, as calculations had to be done manually without a reference. Hence, industry averages were taken from IREA 2023 global report on renewable energy system financials. Understandably, offshore wind farms have a higher investment cost, higher maintenance costs, and a longer payback time, than onshore wind power. Levelized Cost of Electricity (LCOE) for offshore wind farm is 0.051 €/kWh, for onshore: 0.027 €/kWh, and for solar farm: 0.038 €/kWh. Payback Time for 1GW offshore wind project 12.3 yrs is considerably longer than that of 1GW onshore: 5.6 yrs, and 50MW solar farm: 9.9 yrs. Whereas onshore and solar fit into industry average payback time, offshore does not. This could be caused by caused by the high industry maintenance costs of offshore wind power (twice that of onshore wind farm), which limits annual profits, while prolonging the investment's payback time.

Practical application of the Social-LCA methodology in the social impact assessment proved too significant of a study for this research. Therefore, *Labour conditions* were all based on assumptions regarding raw material extraction. Judging an energy projects' conditions based on approximations is cause for human error and subjective prejudice. Yet, unfortunately, a complete S-LCA would not have been worth the diminishing improvements of the results. Conversely, the *Public acceptability* survey succeeded in every way. In total 105 respondents from Estonia (5%) and neighbouring Latvia (81%), gave their opinion of the Gulf of Riga offshore wind farm and the hypothetical scenarios. The support percentages proved to be very close to the actual, publicly available, Enefit Green's survey.

Finally, the SA framework favoured 1GW offshore wind farm as the most sustainable relative to a hypothetical 1GW onshore wind farm and 50MW solar farm. The result is largely affected by the manually placed importance values of criteria, but surprisingly, the objective unweighted calculation agreed with the AHP method.

However, is crucial to acknowledge the framework's limitations. Even though AHP is the most used method for Multi-Criteria Decision Analysis in energy industry, it is subjective and prone to human judgement errors. The method enables case-specific adjustments by manually weighing the important of criteria. Yet, this flexibility promotes subjectivity, which is opposed unwanted in a holistic and objective SA framework. This shortcoming led to the development of an additional calculation besides the AHP method - the unweighted comparison. When interpreting the results of a scenario’s sustainability index, both subjective (AHP) and objective (ratio) calculation results should be taken into consideration.

Another cause for possible errors is the reliance on existing data sources and assumptions in impact assessment. For example*, Land use* and *Job creation* are criteria, which are challenging to calculate – therefore, an industry average is used for approximation. This introduces uncertainties in the accuracy of the assessment. This can be avoided by conducting more intricate analysis on the projects by analysing similar renewable energy projects’ publicly available data.

Conducting a precise and accurate Environmental LCA and S-LCA is vastly dependent on the boundaries, scope, and inventory assessment. Some material flows and processes are so challenging to calculate that the effort is not worth the benefit. For example, End-Of-Life recycling was omitted from the scope of this LCA due to lack of literature material regarding the calculation process. As long as the scope and definitions stay constant between scenarios, the loss in LCA’s accuracy does not significantly affect the result.

Practically, the sustainability assessment tool encourages companies like Enefit Green to leverage the comparison results in making better-informed decisions for long-term sustainability. Future developments of the tool could delve into expanding the framework's applicability to different geographic contexts, energy scales, or technology advancements. The continuous evolution of renewable energy technologies requires ongoing research, and there is no doubt that tools like this will play a key role in steering the world towards a greener future.

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APPENDICES

Appendix 1. Sub-criteria ratio table.

Emission damage

Global Warming Potential	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	1.889	20.333
Scenario #2	0.529	1	10.765
Scenario #3	0.049	0.093	1

Photochemical ozone creation	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	2.532	4.947
Scenario #2	0.395	1	1.954
Scenario #3	0.202	0.512	1

Acidification potential	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	2.381	4.856
Scenario #2	0.420	1	2.039
Scenario #3	0.206	0.490	1

Eutrophication potential	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	2.556	3.778
Scenario #2	0.391	1	1.478
Scenario #3	0.265	0.676	1

Terrestrial ecotoxicity	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	2.679	6.385
Scenario #2	0.373	1	2.383
Scenario #3	0.157	0.420	1

Freshwater ecotoxicity	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	2.308	16.000
Scenario #2	0.433	1	6.932
Scenario #3	0.063	0.144	1

Marine ecotoxicity	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	2.857	11.714
Scenario #2	0.350	1	4.100
Scenario #3	0.085	0.244	1

Land use

Land use	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	0.367	0.037
Scenario #2	2.725	1	0.100
Scenario #3	27.255	10.000	1

Resource use efficiency

Abiotic resource depletion	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	2.667	5.667
Scenario #2	0.375	1	2.125
Scenario #3	0.176	0.471	1

Water consumption	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	2.800	5.747
Scenario #2	0.357	1	2.053
Scenario #3	0.174	0.487	1

Energy consumption	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	1.452	0.067
Scenario #2	0.689	1	0.046
Scenario #3	14.951	21.713	1

Energy payback time	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	1.705	4.721
Scenario #2	0.587	1	2.769
Scenario #3	0.212	0.361	1

Economic viability

Capital costs	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	0.416	0.230
Scenario #2	2.403	1	0.554
Scenario #3	4.341	1.807	1

Total annualized costs	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	0.537	0.115
Scenario #2	1.861	1	0.214
Scenario #3	8.701	4.675	1

Levellized Cost of Electricity	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	0.529	0.745
Scenario #2	1.889	1	1.407
Scenario #3	1.342	0.711	1

Payback period

Investment payback period	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	0.455	0.805
Scenario #2	2.196	1	1.768
Scenario #3	1.242	0.566	1

Local economic impact

Reliability of electricity producton	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	1.000	2.000
Scenario #2	1.000	1	2.000
Scenario #3	0.500	0.500	1

Job creation	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	1.000	28.500
Scenario #2	1.000	1	28.500
Scenario #3	0.035	0.035	1

Labour conditions

Labour conditions	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	1.000	1.250
Scenario #2	1.000	1	1.250
Scenario #3	0.800	0.800	1

Human health impact

Human toxicity	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	3.235	6.706
Scenario #2	0.309	1	2.073
Scenario #3	0.149	0.482	1

Public acceptability

Public acceptability	Scenario #1	Scenario #2	Scenario #3
Scenario #1	1	1.353	0.932
Scenario #2	0.739	1	0.689
Scenario #3	1.072	1.451	1

Appendix 2. LCIA results of energy project scenarios.

TABLE 21. 1GW offshore wind farm environmental impacts.

Impact category	**Raw material extraction**	**Manufacturing**	**Transportation**	**Construction**	**TOTAL**
Global warming potential (tonnes CO_2eq)	3.31 x10^5	2.07 x10^4	2005.4	4709	**3.59 x10^5**
Abiotic resource depletion (GJ)	2.81 x10^6	1.75 x10^5	3.71 x10^4	2456.54	**3.02 x10^6**
Photochemical Oxidant Creation Potential (t C_2H_4eq)	91.76	3.86	-	1.0	**96.6**
Accidification potential (t SO_2eq)	882.4	55.15	0.739	14.7	**952.9**
Eutrophication potential (t PO_4eq)	79.67	4.98	-	2.67	**87.33**
Terrestrial ecotoxicity (t 1,4-DBeq)	732.62	45.79	-	3.0	**781.4**
Freshwater ecotoxicity (t 1,4-DBeq)	1236.75	77.3	-	15.46	**1329.5**
Marine ecotoxicity (t 1,4-DBeq)	3.29 x10^4	5.02 x10^3	-	33.64	**3.5 x10^4**
Human toxicity (t1,4-DBeq)	1.63 x10^5	2.06 x10^3	-	56.21	**1.74 x10^6**
Water consumption (t)	8.93 x10^5	5.58 x10^4	-	527	**9.5 x10^5**
Energy consumption (TWh)	1.294	0.456	0.010	0.273	**2.033**

TABLE 22. 1GW onshore wind farm environmental impacts.

Impact category	**Raw material extraction**	**Manufacturing**	**Transportation**	**Construction**	**TOTAL**
Global warming potential (tonnes CO_2eq)	5.35 x10^5	3.34 x10^4	1288.3	7596	**5.77 x10^5**
Abiotic resource depletion (GJ)	6.08 x10^6	3.8 x10^5	2.38 x10^4	5317.2	**6.49 x10^6**
Photochemical Oxidant Creation Potential (t C_2H_4eq)	187.17	11.7	-	3.04	**201.9**
Acidification potential (t SO_2eq)	1823	113.9	0.305	30.38	**1967.7**
Eutrophication potential (t PO_4eq)	181.1	11.32	-	6.08	**198.5**
Terrestrial ecotoxicity (t 1,4-DBeq)	1665	104.1	-	6.84	**1775.9**
Freshwater ecotoxicity (t 1,4-DBeq)	2430.72	151.92	-	30.34	**2613.0**
Marine ecotoxicity (t 1,4-DBeq)	8.03 x10^4	5.02 x10^3	-	80.04	**8.53 x10^4**
Human toxicity (t1,4-DBeq)	4.42 x10^5	2.76 x10^4	-	151.92	**2.26 x10^6**
Water consumption (t)	2.13 x10^6	1.33 x10^5	-	3798	**6.2 x10^6**
Energy consumption (TWh)	1.839	0.611	0.0066	0.506	**2.962**

TABLE 23. 50MW photovoltaic solar farm environmental impacts.

Impact category	Raw material extraction	Manufacturing	Transportation	Construction	TOTAL
Global warming potential (tonnes CO_2eq)	8.79 x10^4	7032	0.115	210.9	**9.51 x10^4**
Abiotic resource depletion (GJ)	1.93 x10^5	2.1 x10^4	2128	1061.5	**2.17 x10^5**
Photochemical Oxidant Creation Potential (t C_2H_4eq)	5.69	3.41	-	0.018	**6.0**
Acidification potential (t SO_2eq)	57.2	4.0	0.00245	0.04	**61.2**
Eutrophication potential (t PO_4eq)	4.16	0.21	-	0.01	**4.4**
Terrestrial ecotoxicity (t 1,4-DBeq)	59.2	5.33	-	0.21	**64.7**
Freshwater ecotoxicity (t 1,4-DBeq)	258	18.06	-	0.54	**276.6**
Marine ecotoxicity (t 1,4-DBeq)	4743.6	521.8	-	5.22	**5270.6**
Human toxicity (t1,4-DBeq)	1.41 x10^4	705.6	-	14.11	**1.48 x10^4**
Water consumption (t)	5.9 x10^4	1.2 x10^4	-	118.2	**7.1 x10^4**
Energy consumption (GWh)	69.57	47.59	0.59	4.88	**122.64**

TABLE 24. LCIA results – total environmental impact.

Impact category	1GW offshore wind farm	1GW onshore wind farm	50MW PV solar farm
Global warming potential (tonnes CO_2eq)	3.6 x10^5	5.8 x10^5	9.51 x10^4
Abiotic resource depletion (GJ)	3.0 x10^6	6.5 x10^6	2.17 x10^5
Photochemical Oxidant Creation Potential (t C_2H_4eq)	96.6	201.9	6.0
Acidification potential (t SO_2eq)	952.9	1967.7	61.2
Eutrophication potential (t PO_4eq)	87.3	198.5	4.4
Terrestrial ecotoxicity (t 1,4-DBeq)	781.4	1775.9	64.7
Freshwater ecotoxicity (t 1,4-DBeq)	1329.5	2613	276.6
Marine ecotoxicity (t 1,4-DBeq)	3.5 x10^4	8.5 x10^4	5270.6
Human toxicity (t1,4-DBeq)	1.7 x10^6	2.3 x10^6	1.48 x10^4
Water consumption (t)	9.5 x10^5	6.2 x10^6	7.1 x10^4
Total energy consumption (GWh)	2033	2962	122.6

Appendix 3. Public questionnaire.

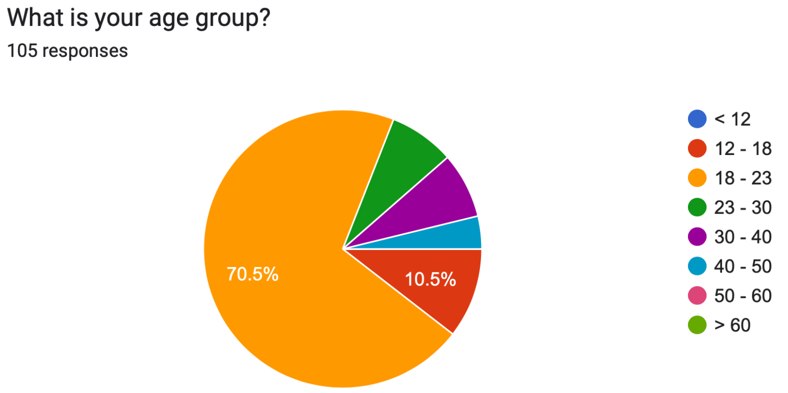

FIGURE 9. Age of respondents. Majority is younger than 23, signalling that the results of the survey might be more supportive of progressive technologies than the general public – as older people are known to be more conservative.

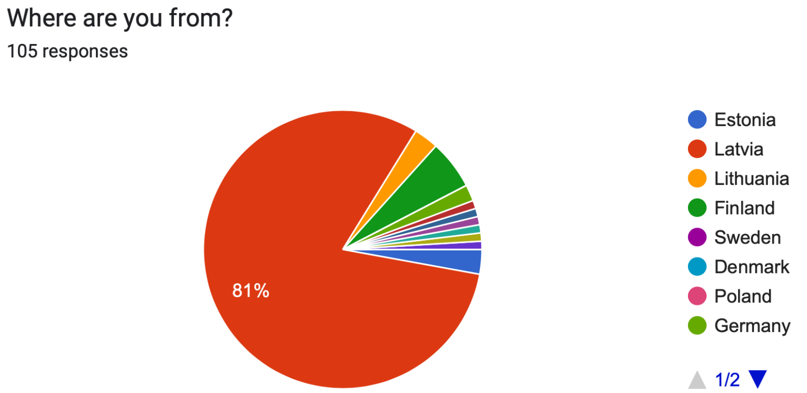

FIGURE 10. Country of residence. Majority is from Latvia, which is close to the affected area of the Gulf of Riga offshore windfarm.

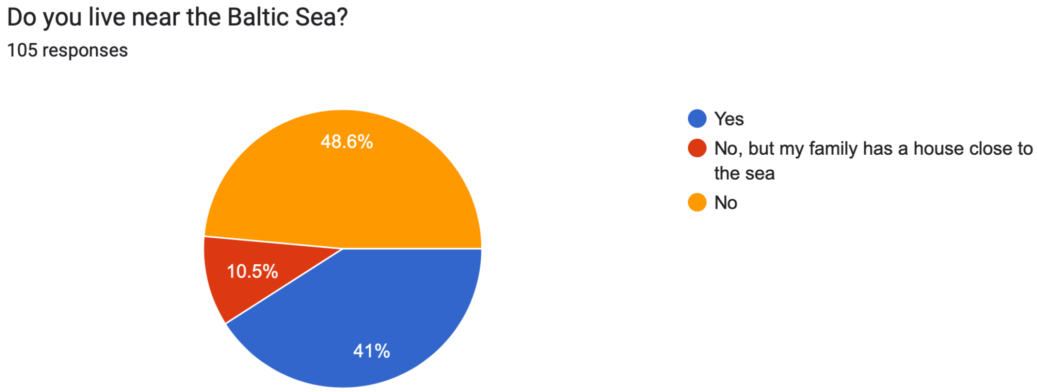

FIGURE 11. Location of residence in relation to the Baltic Sea. More than 51% are true locals of the sea – and hypothetically – the 1GW offshore windfarm.

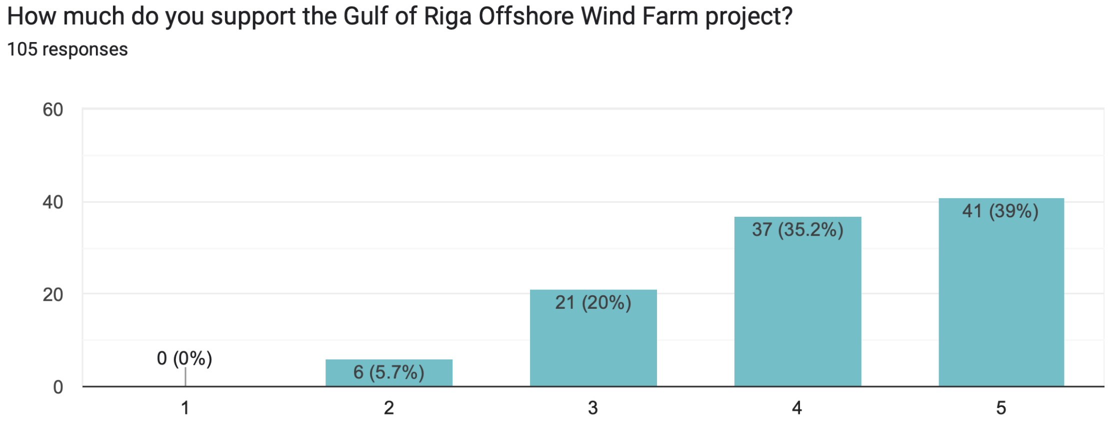

FIGURE 12. General support for the 1GW Offshore windfarm. **74% in support** (%percentage of respondents answering 4 and 5). True locals in support - **69%**.

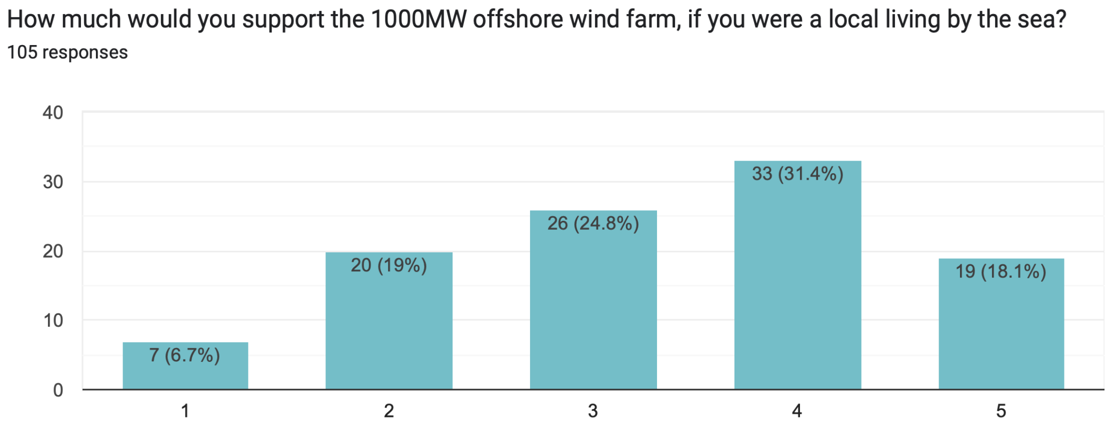

FIGURE 13. Support for the 1GW Offshore windfarm if “they were locals”: **67% of respondents in support**.

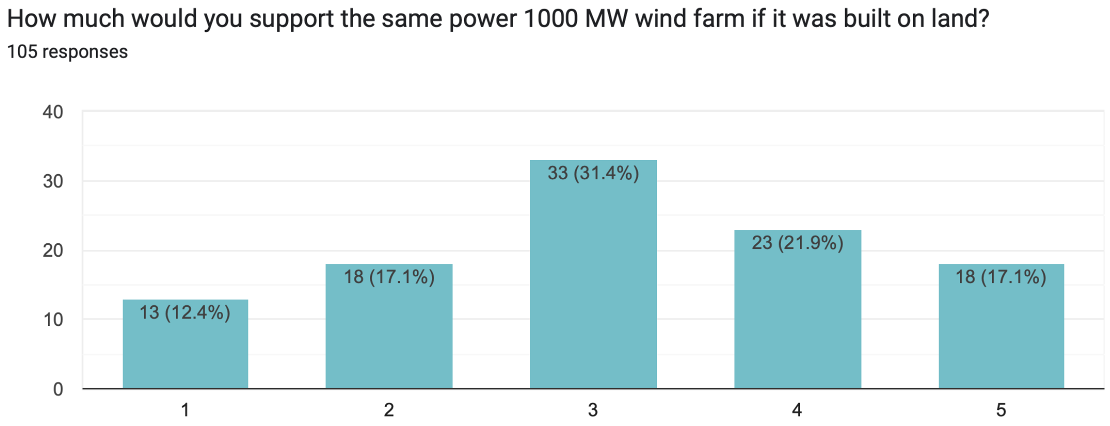

FIGURE 14. General support for the 1GW offshore windfarm: **63% in support**.

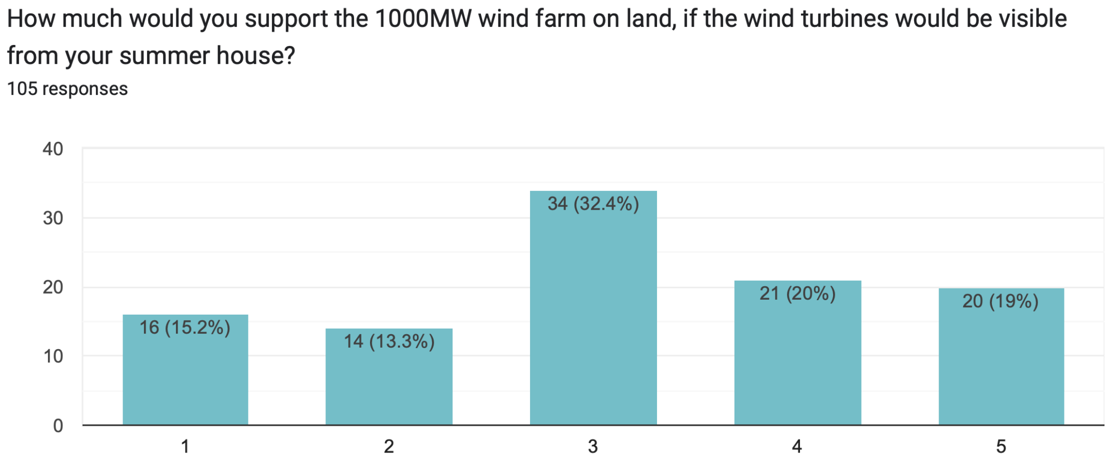

FIGURE 15. Hypothetical local support for the offshore windfarm: **51% in support**.

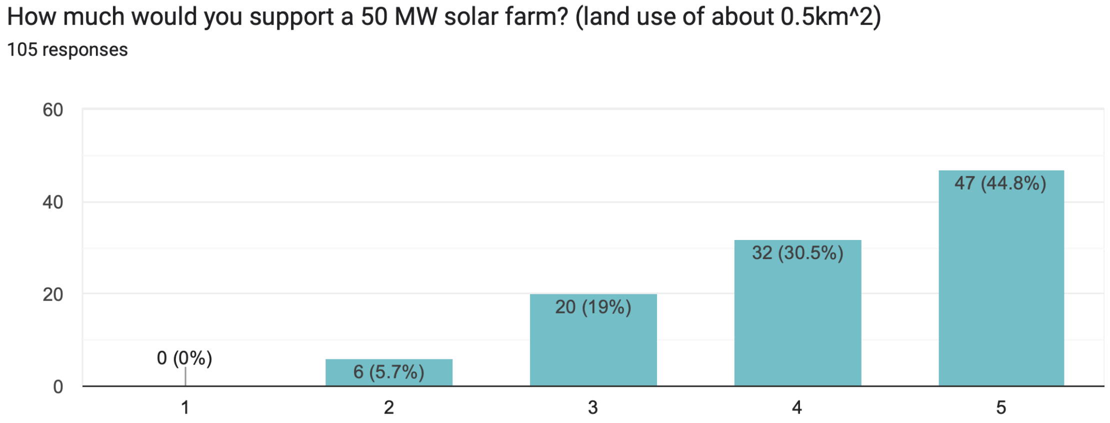

FIGURE 16. General support for the 50MW solar farm: **79% in support**.

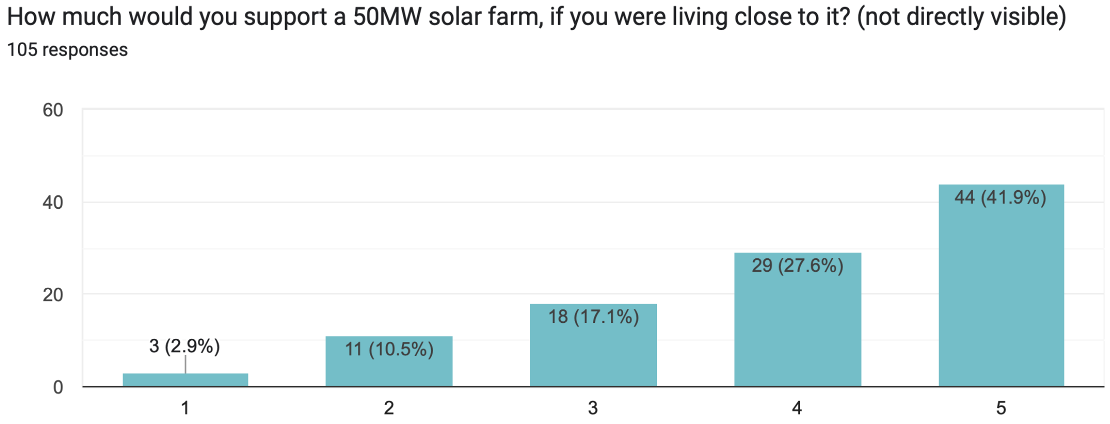

FIGURE 17. Hypothetical local support for the 50MW solar farm: **74% in support**.