Preliminaries in Data-Driven Prioritization of Sustainability Indicators for Stationary Energy Storage: An Interpretable Machine Learning Approach

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Abstract. The study proposes a novel method for identifying sustainability indicators for stationary energy storage devices in their early design stages. Literature-based data were collected and established in a database, then analyzed using the Apriori algorithm for association rule mining implemented in Python. Scope- and dimension-based evaluations revealed a well-balanced co-existence of environmental, social, economic, and ethical indicators under the scope of "optimization of integrated sustainability outcome." The algorithm generated more than 100 rules, and by applying a support threshold of 0.25, a final set of indicators covering all four dimensions was derived. Some of the selected indicators include: GHG emissions, Renewable energy penetration, Energy efficiency, Levelized Cost of Storage, Operational/maintenance costs, Payback period, Resource consumption, Investment cost, Installation cost per kW, System lifetime, Supply chain transparency and traceability, Use-phase emissions, Accessibility of clean energy, Combined environmental impact, and Fairness in demand flexibility distribution. The method is non-biased, data-driven, and replicable, offering a robust foundation for sustainability evaluations.

Keywords: stationary energy storage devices, sustainability indicators, machine learning, Apriori

1 Introduction

Integration of artificial intelligence (AI) and machine learning (ML) has already taken place in many scientific fields. However, its use for evaluation of sustainability in the design stage of renewable energy facilities or related applications such as stationary energy storage devices (SESDs) is comparably limited[1]. Especially some specific tasks, like identifying suitable indicators to evaluate sustainability of technologies in early stages, are still completely carried out by human involvement. This increases the risk of bias and can lead to the use of irrelevant or arbitrary indicator sets [2]. In this study, we propose a novel method of using association rule mining (ML algorithms) to extract and to evaluate indicator sets that have been used so far in existing literature for assessing the sustainability of SESDs in their early designing stages. The method is novel, data driven and replicable alternative to manual indicator selection.

The Apriori algorithm, which comes under association rule mining, was first used in market analysis to understand frequently bought items along with buying rules. Later, it was applied in many qualitative items set identifications under different contexts [3]. As sustainability indicators can also be defined as qualitative item sets [4], the use of the Apriori rule mining method can identify shared patterns in different indicator sets used in SESD sustainability evaluation.

By integrating this approach into renewable energy applications, the study demonstrates how AI-driven or ML methods can support transparent, data-based decision making for sustainable energy system design and policy development.

2 Methodology

2.1 Database establishment

To apply a machine learning algorithm, a database is required. Hence, literature for the database establishment was gathered through the Scopus platform. A number of keywords covering different sustainability dimensions such as environmental, economic, social, and ethical were used for the article search. Initially, 926 articles were gathered covering the period from 1990 to 2026. After, sorting was done using stringent indicators as keywords. Articles that focus on only one sustainability dimension were rejected. Further, articles that are not focusing on stationary storage devices were also rejected from reviewing. After the initial screening, 151 articles covering different regions of the world were included in the database. Through the included articles, 123 sustainability indicators covering multi-dimension evaluation were identified. Moreover, included articles were categorized based on manually set generalized scope groups and the number of sustainability dimensions (initially decided four dimensions) covered for the easiness of the analysis. The final form of the database included 4 columns of metadata like article number, title, scope, and dimensions covered. The remaining column headings included the indicator names, and binary form was used to fill the database such that if the indicator is present it has “1” and if not “0”. The binary form is helpful for the analysis using programming languages.

2.2 Machine learning approach

In the current study, the Apriori algorithm for association rule mining is being accompanied [5]. Python 3.13 programming software is used as the platform to implement the algorithm. The Apriori algorithm was first used in market analysis to identify frequently bought items in the shopping cart context. However, later it was frequently used in qualitative evaluation of co-occurring item sets in databases [6, 7]. Along in this article, we examined the applicability of the Apriori algorithm in identifying frequently co-occurring indicators and identifying any associated rules. The rules mined from the data using the Apriori will be given in a suggestive relationship. For instance, if Indicator 1 (antecedent) occurs, Indicator 2 (consequent) is likely to occur with higher support and confidence, given that both Indicator 1 and 2 are subsets of the full indicator list and their intersection is null. “Lift,” on the other hand, explains the significance of the rule. It explains how many times the co-occurrence is likely to appear more than by chance. Equations 1, 2, and 3 denote the calculation of the support, confidence, and lift.

$$Support\ (Ind.1 \rightarrow Ind.2) = \frac{Frequencey\ of\ (Ind.1 \cup Ind.2)}{n} \qquad (1)$$

$$Confidence\ (Ind.1 \rightarrow Ind.2) = P\ (Ind.1|Ind.2) = \frac{Frequency\ (Ind.1 \cup Ind.2)}{Frequency\ (Ind.1)} \quad (2)$$

$$Lift\ (Ind.1 \rightarrow Ind.2) = \frac{suport\ (Ind.1 \cap Ind.2)}{Support\ (Ind.1) \times Support\ (Ind.2)} \quad (3)$$

Where, Ind.; Indicator, P; probability, and n; number of total transactions (or number of papers included). Threshold values for the minimum allowing support and minimum allowing confidence were decided after several runs of the Apriori algorithm on the dataset.

Once the database is implemented in Python with the pre-decided values for support and confidence, indicators that are likely to occur based on the scope of the articles were firstly selected. Then, the Apriori algorithm was used again to understand sustainability-dimension-specific indicator lists. Finally, the overall indicator list was established based on the findings from the above two categories and the overall indicator co-occurrence likelihood.

3 Results

The majority of the articles included in the database were from Europe (48%). The second highest number of articles was recorded from Asia at 29%. The rest of the world (America, Oceania, Africa, and the Middle East) consisted of 23%. Articles were categorized into seven scopes, and many articles discussed different combinations of sustainability dimensions. Table 1 below shows the scopes identified along with the percentage of articles under each scope. Moreover, it shows the different combinations of dimensions discussed and the percentage of articles belonging to each group.

Table 1. Set of Scope and dimensions covered by the article with the corresponding percentage.

Scope	Percentage	Dimensions	Percentage
Optimization of devices to enhance overall sustainability (i)	7%	Environmental & Economic (A)	58%
Development of institutional and financial frameworks for energy sector sustainability (ii)	5%	Environmental, Economic and Social (B)	21%

Evaluation of overall sustainability of stationary energy storage systems (iii)	53%	Environmental, Economic, Social and Ethical (C)	17%
Optimization of energy systems and communities for integrated sustainability outcomes (iv)	25%	Other combinations (D)	4%
Development of comprehensive prospective assessment frameworks for energy technologies (v)	6%		
Road mapping and technology assessment for next-generation sustainable rechargeable battery research and industry in Europe (vi)	3%		
Optimization of multi-vector stationary energy storage systems for cost, efficiency, and resource utilization under uncertainty (vii)	1%		

As per Table 1, the database has more articles under Scope iii, about “evaluation of overall sustainability of stationary energy storage systems,” which is appropriate for this study as the indicator set will be determined for the sustainability evaluation of SESDs. However, considering the dimensions addressed, a higher number of articles focused only on environmental and economic sustainability. This may hinder most of the social and ethical indicators that should otherwise be involved in a total sustainability assessment of SESDs. Accordingly, it will be useful to understand scope-based indicator sets and dimension-based indicators to evaluate the final set of indicators for assessing the sustainability of SESDs.

To determine the scope- and dimension-based indicators, the minimum support was set as 0.1 and the confidence above 0.5. Accordingly, all the indicator combinations below these limits were ignored by the algorithm. As a matter of fact, only Scope i, iii, and iv succeeded in providing corresponding antecedents and consequents. Figure 1 shows the heat map of top 10 rules provided by the Apriori algorithm for selected dimension groups and scope numbers.

As per the figure and overall outcome the minimum lift in the identified rule is 5.5 for Scope i, which confirms that the identified rule is 5.5 times more likely to occur than by coincidence. The rule explains a strong co-existence of economic indicators (as antecedent) with both social and ethical indicators (as consequent). Mostly, when environmental indicators become the antecedent, the consequent is also an environmental indicator. In the case of Scope iii, the minimum lift reported is 7.9 and the highest recorded as 9.8, increasing the chance of the identified rule occurring. Under Scope iii, a strong co-existence of environmental indicators can be seen. Though this scope has the implication of studying overall sustainability, the rule suggests that most of the corresponding articles have used environmental indicators the most, giving low concern to economic, social, and ethical indicators.

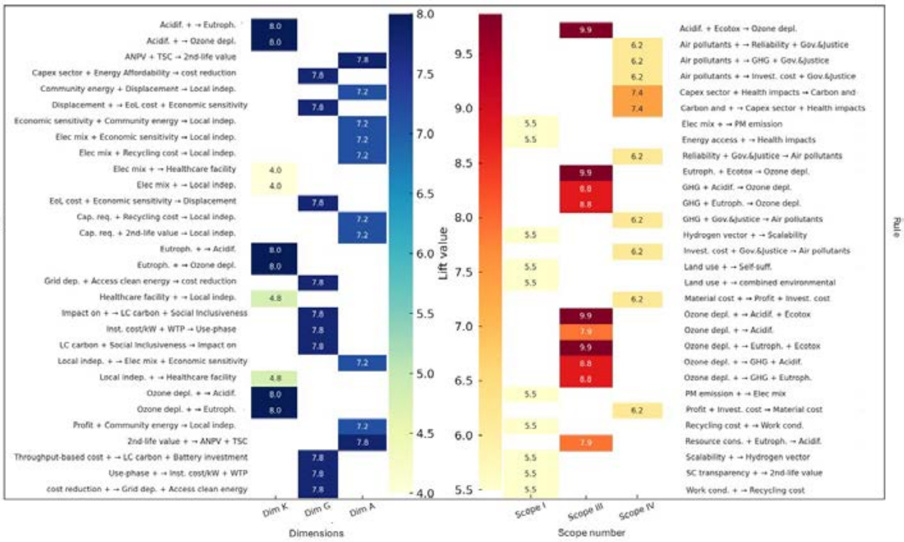

Fig. 1. Heat map of top 10 rules and lift values generated by the Apriori algorithm for selected dimension groups and scope numbers.

Scope iv's lift varies from 5.2 to 7.4, suggesting a higher likelihood of the identified rules occurring. Moreover, the articles that focus on integrated sustainability assessment have a more robust and holistic indicator selection. Results show a strong co-existence of environmental indicators with both economic and social indicators.

Dimension-specific indicators were also identified by the algorithm with a higher lift under each case. Class A, where environmental and economic indicators are mainly addressed by the articles, was found to have a lift from 7.0 to 7.8. As expected, a strong co-occurrence of main environmental and economic indicators was observed. Class B, where social indicators are also involved along with environmental and economic indicators, showed a lift of 7.5 under each rule. Moreover, main environmental, economic, and social indicators can be seen in the group with high co-existence possibilities. Interestingly, some ethical indicators were also listed along with environmental and economic indicators. Class C showed indicators from all four categories co-existing in most cases. However, lifts for co-occurrence of environmental (antecedent)–environmental (consequent) rules are backed by higher values (at 8), while economic, social, and ethical indicator listings have lower lifts (4.0–4.8). Class D has a lower support than 0.1 and hence was not identified by the algorithm. Table 2 below shows the main indicators that can be categorized under different scopes and dimensions.

Table 2. Indicators identified by the Apriori algorithm for specific scope and dimension classes.

Scope category	Indicators	Dimension class	Main indicators
(i)	GHG emissions, Renewable energy penetration, Energy cost savings, Life cycle carbon emissions, Operational/maintenance costs, Payback period, Grid electricity dependence, Levelized Cost of Storage, Investment cost, Water use, Net present cost, Energy reliability, Resource consumption, Use-phase emissions, Energy storage capacity required, Installation cost per kW, Profitability, Capital investments in the energy sector, Electricity cost from grid, Community energy sharing, Job creation, Accessibility of clean energy, Community empowerment, Stakeholder engagement, Child labor score	(A)	GHG emissions, Operational/maintenance costs, Levelized Cost of Storage, Energy efficiency, Life cycle carbon emissions, Renewable energy penetration, Energy storage capacity required, Payback period, Energy self-sufficiency, Grid electricity dependence, Installation cost per kW, Energy cost savings, Capital investments in the energy sector, Investment cost, Resource consumption, Total System Cost, Net present cost, System lifetime, Cumulative energy demand, Use-phase emissions, Throughput-based cost sensitivity, Economic sensitivity, Exergetic round trip efficiency, End-of-life treatment cost, Combined environmental impact
(iii)	Energy efficiency, GHG emissions, Levelized Cost of Storage, Life cycle carbon emissions, Payback period, Operational/maintenance costs, Resource consumption, Energy self-sufficiency, Energy storage capacity required, Installation cost per kW, Renewable energy penetration, Grid electricity dependence, Energy cost savings, System lifetime, Capital investments in the energy sector, Cumulative energy demand, End-of-life treatment cost, Economic sensitivity, Net present cost, Total System Cost, Recycling rate, Annualized net present value, Investment cost, Supply chain transparency and traceability, Use-phase emissions	(B)	Renewable energy penetration, GHG emissions, Energy efficiency, Energy storage capacity required, Levelized Cost of Storage, Energy self-sufficiency, Grid electricity dependence, Operational/maintenance costs, Life cycle carbon emissions, Public acceptance, Energy Density, Job creation, Exergetic round trip efficiency, Recycling rate, End-of-life treatment cost, Energy Affordability, System lifetime, Community empowerment, Fairness in demand flexibility distribution, Local governance and stakeholder justice, Resource consumption, Payback period, Energy cost savings, Investment cost, Accessibility of clean energy
(iv)	Renewable energy penetration, GHG emissions, Energy storage capacity required, Operational/maintenance costs, Grid electricity dependence, Levelized Cost of Storage, Total System Cost,	(C)	GHG emissions, Resource consumption, Accessibility of clean energy, Investment cost, Supply chain transparency and traceability, Fairness in demand flexibility distribution, Local governance and stakeholder justice,

Energy self-sufficiency, Investment cost, Capital investments in the energy sector, Energy efficiency, Energy reliability, Energy cost savings, Fossil fuel use, Accessibility of clean energy, Energy Affordability, Supply chain transparency and traceability, Life cycle carbon emissions, Resource consumption, Payback period, Cost reduction, Job creation, Public acceptance, Digitalization of Energy Storage, Use-phase emissions	Renewable energy penetration, Public acceptance, Corporate social responsibility compliance, Energy efficiency, Levelized Cost of Storage, Operational/maintenance costs, Energy storage capacity required, Payback period, Profitability, Recycling cost, Energy reliability, Community empowerment, Health impacts from pollution, Energy Affordability, Life cycle carbon emissions, Grid electricity dependence, Energy cost savings, Capital investments in the energy sector

Running of the Apriori algorithm on the overall database has given many combination rules with lifts varying from 6.0 to 7.5. The highest lift combinations showed strong relationships of economic indicators with other types of indicators. However, the algorithm identified over 100 rules existing in the database. Accordingly, indicators with support over 0.25 were selected to be the final indicator list. The 0.25 cutoff for support makes sure that most of the indicators from all four dimensions are included in the final set of indicators, as 0.25 is the minimum support reported by any of the three-dimension class indicator sets. Hence, the final indicator set categorized under four dimensions considered is: Environmental→GHG emissions, Renewable energy penetration, Energy efficiency, Energy storage capacity required, Life cycle carbon emissions, Grid electricity dependence, Energy self-sufficiency, Resource consumption (mineral and material intensity), System lifetime, Use-phase emissions (charging/discharging losses) , Recycling rate, Combined environmental impact; Economical→Levelized Cost of Storage (LCOS), Operational/maintenance costs, Payback period, Investment cost, Energy cost savings, Capital investments in the energy sector, Installation cost per kW, Total System Cost, End-of-life treatment cost; Social→ Accessibility of clean energy; Ethical→ Supply chain transparency and traceability, Fairness in demand flexibility distribution.

4 Conclusion, limitations and suggestions

The study brings a novel method in identifying indicators to evaluate the sustainability of SESDs in their early design stages. The method proposed is non-biased, data-driven, and replicable. The study evaluated scope-based and dimension-based indicator sets that are readily applicable in future studies. However, for studies apart from the scopes listed in the manuscript, the overall indicator list needs to be used, which may not satisfy the real scope of the study. Nevertheless, the outcome of the research provides an indicator set that covers all four dimensions of interest for sustainability evaluation. However, less number of indicators were included from social and ethical aspects. One challenge is that the initially set support value (0.1) can largely influence the outcome. Hence, a higher support value (0.2 or 0.3) can provide a better indicator set that closely aligns with the scope and the dimensions. However, the resulting indicator list in this case can be relatively shorter. To overcome this problem, other algorithms such as classification rule mining may be applied. This could potentially enhance the social and ethical indicators included in the final list. Moreover, the database uses data from 151 articles, which can also be a limitation. Using a larger dataset can be beneficial in identifying a more prominent set of indicators.

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