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Assessing Renewable Energy Impact in Nordic-Baltic Region: Sensitivity Analysis and MCDM Approach

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Abstract
The article aims to analyze the development of renewable energy in the Nordic-Baltic countries using the MCDM methods. The analysis was conducted on eight alternatives (Norway, Sweden, Denmark, Finland, Iceland, Estonia, Lithuania, and Latvia) and ten criteria (primary energy consumption, energy intensity, final energy consumption, share of energy from renewable sources, renewable energy source in transport, share of fossil fuels in final energy consumption, energy productivity, imports of solid fossil fuels by partner country, electricity prices for household consumers, GDP per capita). The improved entropy method was used to determine the criterion weights, and the PIV method was used to rank the alternatives. A comprehensive sensitivity analysis was applied to test the robustness of the model. The impact of 34 different variations in criterion weights on the results was examined and the smallest weight change required to alter the current ranking is 18.93%. The findings demonstrate that Norway emerges as the most appropriate alternative, while Lithuania ranks last. It has been determined that countries that invest the most in renewable energy are ranked at the top. It has been concluded that the obtained results are entirely objective and rational, and the applied model is applicable in the field of renewable energy.

Keywords: *Renewable energy development, Sensitivity analysis, MCDM.*

1. Introduction

Due to the rising global population and advancements in civilization, there has been a rapid increase in energy demand [1]. The requirement for energy to fulfill human welfare, health, and social/economic development is steadily growing [2]. All societies rely on energy-related services to meet their essential requirements (such as space comfort, mobility, health, cooking, communication, and lighting) and to serve specific purposes [3].

Energy consumption increases in direct proportion to the escalation in greenhouse gas (GHG) emissions. GHG, existing as gaseous compounds in the atmosphere, absorb and trap infrared energy emitted from the Earth, causing warming of the atmosphere and the greenhouse effect, which plays a role in global warming [4]. Depletion of resources, as well as the negative effects that threaten the environment and human health [5], GHGs emitted such as carbon dioxide (CO_2) plays a significant role in influencing climate change in both the developed and developing countries [6].

In this regard, all nations have begun implementing various strategies to tackle these issues. Governments have also started reviewing their energy strategies and policies to address these problems [1]. The primary objective of any climate change mitigation strategy is to reduce GHG emissions. In the process of decarbonization, combating conventional fossil energy sources is crucial [7].

The primary source of GHG emissions that contribute to climate change and global warming is energy derived from fossil fuels. To address this issue, the international community has demonstrated commitments to shifting towards harnessing renewable energy sources in place of conventional fossil fuels [8]. Renewable energy sources are indispensable in reducing climate change, as they are resources that can be rapidly replenished and derived from natural processes [9]. Renewable energy sources have gained significant importance, and now play a crucial role in the overall primary energy sources, currently accounting for 15% of the world's primary energy. The majority of this comes from bioenergy (10%) and hydropower (3%), while the remaining fraction comprises alternative renewable sources (2%) including photovoltaic and wind energy [10].

Renewable energy sources are highly effective tools for addressing environmental problems and produce emissions that contribute to climate change at a lower level than fossil fuels [11]. The issue of developing renewable energy usage, although complex and challenging to quantify using a single factor should be addressed as a multi-dimensional topic described by various indicators [12]. In this context, Multi-Criteria Decision-Making (MCDM) is an appropriate approach for solving such problems as it provides the opportunity for multi-dimensional evaluation.

It is possible to see the applications of MCDM methods in different fields in the literature [13], investigated the concept of a utility function to compare the predicted thermal and physical parameters of plastic waste oil with fixed-ratio diesel blends against diesel values and evaluate the best-ranking fuel mixture. When compared to diesel, the results indicate that the WP40D60 blend has the highest brake thermal efficiency, reaching 31.62% at 80% load, and the lowest NOx emissions under all load conditions [14], used well-known utility functions in MCDM methods to highlight the impact of metal cutting variables such as cutting speed, feed rate, and cutting depth on MRR and Ra during the turning of aluminum-based hybrid composites. [15] investigated the effect of RMDTM welding variables and optimized them for the best output responses, voltage, current, and gas flow rate were chosen as welding variables, and their responses were measured in terms of bead height, bead width, and heat-affected zone using the TOPSIS-Taguchi approach.

In this study, the development of renewable energy in Nordic-Baltic countries is analyzed using the MCDM methods for the year 2020. The Nordic-Baltic region is chosen as a primary energy transformation zone on a global scale due to factors such as its abundant natural resources and the significant impact its future energy policies will have on energy consumption in Europe and worldwide. Furthermore, it will be of great significance in shaping the upcoming decisions regarding energy mix and transformation [16]. Heavy investment in renewable energy in this region and the emphasis on sustainable energy development to implement European Union (EU) energy policy priorities [17] and lack of studies on renewable energy development in Nordic-Baltic countries have also been influential in the choice of Nordic Baltic countries for this study. This paper also incorporates a sensitivity analysis approach to assess the robustness of the employed model.

This study primarily focuses on the following aspects: i) The number of studies examining the development of renewable energy in the literature is limited and no research using Entropy-Proximity Indexed Value (PIV) model in the field of renewable energy has been found. Therefore, it is thought that the study will contribute to the literature by filling this gap. Other reasons why the improved entropy-PIV model was preferred in this study are its suitability for real-world problems and a simple calculation procedure. ii) To test the robustness of the model, the impact of variations in criterion weights on the results was examined through sensitivity analysis. The critical decision criteria and the smallest percentage of weight change that results in a ranking alteration were determined. iii) The weights of the indicators compiled from Eurostat were determined using the objective and reliable technique called Entropy. iv) Provide a practical and flexible methodology that can handle complex decision-making problems. In summary, this study is structured around the following main objectives: i) To evaluate 8 Nordic-Baltic countries regarding their renewable energy development and determine which one is best. ii) Addressing this evaluation with the improved entropy-PIV approach, which has not been used before in renewable energy development. iii) To determine the importance of the evaluation criteria used in the evaluation of countries. iv) To present the development of a simple but practical framework to identify the most developed country in the field of renewable energy.

On the other hand, the contributions of the study can be stated as follows: i) A real-world problem related to countries' renewable energy developments has been presented for the use of the improved Entropy-PIV methodology. ii) To propose a systematic decision-making framework for evaluating renewable energy development in the Nordic-Baltic countries. iii) The improved entropy and PIV methods have been integrated for the first time in renewable energy development. iv) Optimum criterion weights were obtained with the entropy method, away from the subjective judgments of decision-makers. v) The case study considered can be extended and modified for other countries as well.

The remainder of the study is organized as what follows. The studies related to the subject are presented in the second section. Then the preliminaries of the proposed MCDM approach and its application are discussed. In the 5th

Section, the sensitivity analysis application is presented, and the concluding section assesses the results obtained.

2. Materials and methods

Applications of MCDM methods are frequently encountered in the field of energy. It is possible to come across numerous studies where the MCDM methods are used under various topic headings such as financial risk evaluation [18], energy modernization [19], assessing energy security [20], the evaluation of the optimal renewable energy options [21], selection of power plant location [22], strategic planning for low-carbon energy [23], renewable energy technology and policy [24], and hydropower development priority [25]. Table 1 summarizes several studies from the literature that employ MCDM methods in the context of renewable energy.

Table 1. Representative studies on energy topics applying the MCDM methodology.

Study	Case application	Database	Criteria	Methods
[26]	"Evaluating the EU progress towards sustainable energy development"	Eurostat	"Total energy import dependency, aggregate supplier concentration index, electricity interconnection of installed capacity, market concentration index for power generation, market concentration index for a wholesale gas supply unit, energy affordability, cumulative market share of main entities bringing gas in the country, cumulative market share in power generation, cumulative market share in power capacities, household gas prices, household electricity prices, inability to keep home adequately warm"	Pythagorean fuzzy-SWARA-TOPSIS
[27]	"Assessing the extent to which the EU Countries use renewable energy"	Eurostat	"Overall renewable share, renewable energy in transport, renewable electricity generation, renewable heating and cooling"	Entropy, WASPAS
[28]	"Development of renewable energy technologies in Latvia"	Eurostat	"Installed electrical capacity life-cycle CO_2 emissions, investment cost, operation and maintenance cost, renewable energy resources equipment prices by manufacturer, levelized cost of electricity, job creation"	Entropy , TOPSIS
[29]	"Prioritizing the renewable energy heating technologies"	Eurostat	"21 sub-criteria based on energy, economic, environmental, social criterion"	BWM-WASPAS
[30]	"Analysis of the level of renewable energy development"	IRENA	"Total renewable energy, hydropower; renewable hydropower, wind, onshore wind energy, solar photovoltaic, bioenergy; solid biofuels, other solid biofuels, electricity generation"	TOPSIS, VIKOR, VMCM
[31]	"Development of renewable energy sources in EU countries"	Eurostat	"Overall share of energy from renewable sources, share of energy from renewable sources in gross electricity consumption, share of energy from renewable sources in transport, share of energy from renewable sources for heating and cooling, solid biofuels, electricity generation per capita, electricity in road transport, electricity in rail transport, electricity in all other transport modes, transport per capita, heating and cooling per capita, final energy consumption, heating and cooling per capita, heating and cooling per capita heat pumps, heating and cooling per capita"	Taxonomic measure of development) methods
[32]	"Determining a renewable energy perspective for Turkey"	IAEA, UNDESA, IEA, Eurostat and EEA	"Accident fatalities, energy use per capita, supply efficiency of energy, net import dependency, climate change, water quality, soil area where acidification exceeds critical load"	ANP, TOPSIS
[33]	"Evaluation of energy poverty in EU countries"	Eurostat	"Primary energy consumption, final energy consumption final energy consumption in households per capita energy productivity share of renewable energy in gross final energy consumption by sector energy import dependency by products population unable to keep home adequately warm by poverty status greenhouse gas emissions intensity of energy consumption"	ITARA, MARCOS
[12]	"Assessing of renewable energy impact in EU countries"	Eurostat	"Primary energy consumption, energy, intensity, final energy consumption, share of energy from renewable source, renewable energy source in transport, share of fossil fuels in final energy consumption, energy productivity, imports of solid fossil fuels by partner country, electricity prices for household consumers, GDP per capita"	Vector Measure Construction Method (VMCM)
[9]	"Evaluating renewable energy sources in Nordic-Baltic countries"	Eurostat	"Final energy consumption, GHG emissions, energy intensity, the share of energy derived from Renewable energy sources, GDP"	Entropy-VIKOR

As seen from Table 1, Eurostat is commonly used as the database in most of the studies, while entropy and TOPSIS are the frequently employed methods for weighting and ranking purposes. While the subject of renewable energy holds a significant place in the literature, there are also articles summarizing studies in the literature that address the topic of renewable energy development using MCDM methods ([34]; [35]; [36]). The scarcity of studies examining renewable energy development in the literature is notable. In this study, the development of renewable energy has been analyzed using indicators compiled from the Eurostat database, and the selection of indicators has been influenced by the study of [12].

In the literature, it is possible to come across many studies that have used MCDM methods in the energy sector. [37] used the entropy-TOPSIS model to assess sustainable energy security in European countries. At the end of the study, the results showed that the highest level of sustainable energy security was reported for the Czech Republic, and the lowest level was reported for Poland during the examined period. [38] evaluated the performance of 27 EU member countries in terms of the EU 2020 strategy using the VIKOR and TOPSIS methods. Criterion weights were determined by decision-makers. The results indicate that new EU member countries like Slovenia and Romania have achieved higher scores than many of the 15 EU countries. [39] used the entropy-TOPSIS, VIKOR, MOORA, and COPRAS methods to assess the level of sustainable energy development in Central and Eastern European countries for the years 2008 and 2018. The results indicated that the best rankings in 2008 and 2018 belonged to Latvia and Croatia, while the worst rankings belonged to Poland and Bulgaria. [40] used the TOPSIS method to cluster and differentiate EU countries due to the current development potential of the wind energy sector. The results show that the research hypothesis is confirmed for many EU countries, considering the development potential of the wind energy sector. [41] defined the position of EU countries according to the sustainable development goals using the entropy-CoCoSo model. The results highlight Sweden as the country that best implements the specified sustainable development goals and has the best outcomes, while Romania is ranked last. [42] used the VIKOR, TOPSIS, and WASPAS methods to compare the sustainability of the energy sector development between 21 EU member states and China. The results of the MCDM showed that during this period, Romania, the Czech Republic, and Latvia demonstrated the best performance in approaching sustainable energy development goals. [43] used the grey relational analysis method to diagnose the energy security status of the Three Seas Initiative countries and how it changed between 2009 and 2019. Criterion weights were determined using the CRITIC, entropy, and standard deviation methods. During the analyzed period, Austria ranked at the top in terms of energy security, while Poland and Bulgaria ranked at the bottom.

2.1. Improved entropy method

To compare criteria with different dimensions and units, it is necessary to standardize the elements of the decision matrix. However, in MCDM problems, negative and zero values are not often encountered in the decision matrix. In such a case, since negative values cannot be included in the normalized matrix, the elements of the decision matrix need to be converted to positive values. The advantage of the Entropy method is that it reduces the subjective influence of decision-makers and increases objectivity [44]. In this study, the improved entropy method is employed to ascertain the weights of the criteria. The steps of the method are as follows ([45]; [46]).

Step 1: A decision matrix is formulated.

Step 2: The decision matrix elements are standardized using equation (1).

$$\mathbf{x_{ij}} = \frac{\mathbf{X_{ij}} - \mathbf{\overline{X}_i}}{\mathbf{S_i}} \tag{1}$$

X_{ij} and x_{ij} is the original and standardized data. S_i and $\overline{X_i}$ represent the standard deviation values and arithmetic mean, respectively.

Step 3: The decision matrix elements are transformed into positive values using equation (2).

$$\mathbf{x'_{ij}} = \mathbf{x_{ij}} + \mathbf{A}, \mathbf{A} > \left|\mathbf{min x_{ij}}\right| \tag{2}$$

A represents the minimum value within the decision matrix. The notation x'_{ij} represents the standardized value following the conversion. $x'_{ij} > 0$.

Step 4: Normalization is performed using equation (3);

$$\mathbf{P_{ij}} = \frac{\mathbf{x_{ij}}}{\sum_{\mathbf{i=1}}^{\mathbf{m}} \mathbf{x_{ij}}} \tag{3}$$

P_{ij} shows the value of normalized decision matrix elements.

Step 5: The entropy measure is calculated using equation (4).

$$\mathbf{e_j = -k \sum_{i=1}^{n} P_{ij} In P_{ij},} \forall_j \quad (4)$$

$$k = \frac{1}{\ln(m)}$$

k represents a constant, and indicated by the formula.
e_j is the entropy value of the jth criterion.
m indicates the number of alternatives.
Step 6: equation (5) is utilized to determine the differentiation degree of the criteria.

$$\mathbf{d_j = 1 - e_j}, \forall_j \quad (5)$$

d_j shows a contrast density in the j structure.
Step 7: Using Eq. (6), the criterion weights are computed.

$$\mathbf{W_j = \frac{d_j}{\sum_{k=1}^{n} d_k}} \quad (6)$$

W_j shows the criteria weight; $\sum w_j = 1$, $0 \le w_j \le 1$.

2.2. PIV method
The PIV method will be employed in this study to evaluate the countries. The method is based on the positive ideal solution principle, where the best alternative should be close to the optimal solution [47]. The PIV method, in addition to its ease of calculation, provides the advantages of reducing the rank reversal problem observed in many MCDM techniques such as TOPSIS. Furthermore, it provides robust rankings compared to many other MCDM techniques [48]. When compared to traditional techniques like AHP, TOPSIS, COPRAS, and VIKOR, the PIV method offers more reliable solutions in rankings [47]. The steps of the method are as follows ([49]):
Step 1: A decision matrix is formulated.
Step 2: The elements of the decision matrix are normalized using the equation (7).

$$\mathbf{r_i = \frac{x_i}{\sqrt{\sum_{i=1}^{m} x_i^2}}} \quad (7)$$

Step 3: The weighted normalized decision matrix is determined using the equation (8).

$$\mathbf{v_i = w_j * r_i} \quad (8)$$

w_j represents the weight assigned to the jth criterion
Step 4: Weighted proximity index is evaluated using the Eqs. (9) and (10).

$$\mathbf{u_i = v_{max} - v_i} \quad \textbf{Stimulants} \quad (9)$$

$$\mathbf{u_i = v_i - v_{min}} \quad \textbf{Destimulants} \quad (10)$$

Step 5: Overall proximity value is determined using the equation (11).

$$\mathbf{d_i = \sum_{j=1}^{n} u_j} \quad (11)$$

Step 6: Alternatives are ranked.
The alternative with the lowest d_j value takes the top rank.

3. Results and discussion
In this section, the development of renewable energy in Nordic-Baltic countries is assessed using the MCDM methods. The application of the improved entropy-PIV model was employed to outline the process of assessing countries using quantitative data. Eight countries (Norway (a_1), Sweden (a_2), Denmark (a_3), Finland (a_4), Iceland (a_5), Estonia (a_6), Lithuania (a_7), Latvia (a_8)) were evaluated based on the following criteria:
c_1- “Primary energy consumption (MTOE)”
c_{2-} “Energy intensity (KGOE) per thousand euro)”
c_3- “Final energy consumption (MTOE)”
c_4- “Share of energy from renewable source (%)”
c_5- “Renewable energy source in transport (%)”
c_6- “Share of fossil fuels in final energy consumption (%)”
c_7- “Energy productivity (EUR per KGOE)”
c_8- “Imports of solid fossil fuels by partner country (Thousand tonnes)”
c_9- “Electricity prices for household consumers (KWh)”
c_{10}- “GDP per capita (purchasing power standards)”
In this decision, "primary energy consumption (c_1), share of energy from renewable sources (c_4), renewable energy source in transport (c_5), energy productivity (c_7), GDP per capita (c_{10})" are useful criteria with high values desired, whereas "energy intensity (c_2), final energy consumption (c_3), share of fossil fuels in final energy consumption (c_6), imports of solid fossil fuels by partner country (c_8), and electricity prices for household consumers (c_9)" are non-useful criteria where lower values are preferred. The data referred to the year 2020 and were derived from Eurostat [50]. The decision matrix is shown in table 2.
Table 2 also presents the optimization directions of the criteria and their weights, which were determined using the improved entropy. Useful and non-useful criteria are indicated by (+) and (-). Based on the outcomes of the Improved Entropy method, the criteria are listed as follows: c_{10}, c_4, c_3, c_8, c_1, c_7, c_6, c_2, c_9, and c_5.

The basic methodology of the MCDM model established in this paper consists of three parts: (i) improved entropy method employed to weight the criteria, (ii) PIV method utilized to prioritize the alternatives, (iii) Sensitivity analysis conducted to test the robustness of the employed model. The proposed methodology for the study is shown in figure 1.

Table 3 shows the normalized decision matrix obtained using the PIV method.

After the normalization processes, Eq. (8) is employed to obtain the weighted decision matrix, which are indicated in Table 4. On the other hand, weighted and total proximity values have been calculated using Eqs. (9) and (10), and they are presented in Table 5. Table 5 also shows the rankings of countries' renewable energy impact.

Table 2. Decision-making matrix.

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
Opt.	+	-	-	+	+	-	+	-	-	+
w_i	0,0992	0,0930	0,1010	0,1017	0,0893	0,0963	0,0984	0,0994	0,0928	0,1290
a_1	25,0	78,28	18,4	77,358	1214,147	2,67	12,78	1172,414	0,0927	142
a_2	41,3	106,54	30,6	60,124	2127,900	0,97	9,39	2154,000	0,1271	122
a_3	15,4	59,43	13,1	31,681	382,099	0,86	16,83	1122,166	0,0908	133
a_4	29,9	161,92	23,4	43,939	551,729	0,45	6,18	2733,000	0,1205	114
a_5	5,9	461,52	3,0	83,725	35,754	0	2,17	140,128	0,0988	118
a_6	4,3	236,00	2,8	30,069	94,395	0,27	4,24	3,5	0,0953	86
a_7	6,2	199,01	5,3	26,773	110,217	2,52	5,03	194,1	0,0972	88
a_8	4,3	194,70	3,9	42,132	68,008	0,57	5,14	39,767	0,1005	72

Table 3. Normalized decision matrix.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
a_1	0,420	0,141	0,410	0,549	0,470	0,614	0,501	0,346	0,160	0,558
a_2	0,642	0,183	0,630	0,398	0,706	0,292	0,370	0,526	0,651	0,403
a_3	0,289	0,112	0,314	0,149	0,255	0,271	0,658	0,337	0,132	0,488
a_4	0,487	0,267	0,500	0,256	0,299	0,193	0,245	0,632	0,557	0,341
a_5	0,160	0,718	0,133	0,604	0,166	0,108	0,089	0,157	0,247	0,372
a_6	0,138	0,378	0,129	0,135	0,181	0,159	0,170	0,132	0,197	0,124
a_7	0,164	0,323	0,174	0,106	0,185	0,586	0,200	0,167	0,224	0,139
a_8	0,138	0,316	0,149	0,241	0,174	0,216	0,205	0,139	0,271	0,015

Table 4. Weighted decision matrix.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
a_1	0,042	0,013	0,041	0,056	0,042	0,059	0,049	0,034	0,015	0,072
a_2	0,064	0,017	0,064	0,040	0,063	0,028	0,036	0,052	0,060	0,052
a_3	0,029	0,010	0,032	0,015	0,023	0,026	0,065	0,034	0,012	0,063
a_4	0,048	0,025	0,051	0,026	0,027	0,019	0,024	0,063	0,052	0,044
a_5	0,016	0,067	0,013	0,061	0,015	0,010	0,009	0,016	0,023	0,048
a_6	0,014	0,035	0,013	0,014	0,016	0,015	0,017	0,013	0,018	0,016
a_7	0,016	0,030	0,018	0,011	0,017	0,056	0,020	0,017	0,021	0,018
a_8	0,014	0,029	0,015	0,024	0,016	0,021	0,020	0,014	0,025	0,002

Table 5. Weighted and total proximity values and ranking.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	$\sum$	Rank
a_1	0,022	0,003	0,028	0,006	0,021	0,049	0,015	0,021	0,003	0,000	0,1678	1
a_2	0,000	0,007	0,051	0,021	0,000	0,018	0,028	0,039	0,048	0,020	0,2316	3
a_3	0,035	0,000	0,019	0,046	0,040	0,016	0,000	0,020	0,000	0,009	0,1853	2
a_4	0,015	0,014	0,037	0,035	0,036	0,008	0,041	0,050	0,039	0,028	0,3049	7
a_5	0,048	0,056	0,000	0,000	0,048	0,000	0,056	0,002	0,011	0,024	0,2458	4
a_6	0,050	0,025	0,000	0,048	0,047	0,005	0,048	0,000	0,006	0,056	0,2843	5
a_7	0,047	0,020	0,005	0,051	0,047	0,046	0,045	0,003	0,008	0,054	0,3258	8
a_8	0,050	0,019	0,002	0,037	0,047	0,010	0,045	0,001	0,013	0,070	0,2940	6

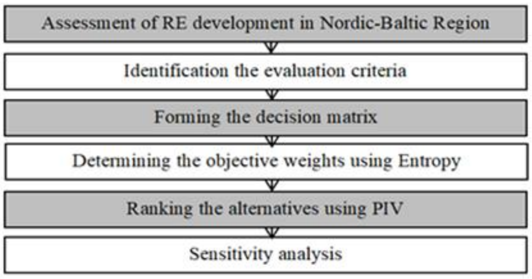

Figure 1. Methodology of research.

According to the results of the proposed model, Norway is the most appropriate alternative. Table 5 clearly demonstrates that the ranking of countries' renewable energy development is as follows: Norway > Denmark > Sweden > Iceland > Estonia > Latvia > Finland > Lithuania. Norway, Denmark, and Sweden achieved the highest aggregate measurements, securing positions within the top three. However, Latvia, Finland, and Lithuania rank towards the bottom in terms of renewable energy development.

There is an article published in the literature that addresses a similar topic with a different sample set. [9] analyzed the economic performance and the fight against climate change in the Nordic-Baltic countries in the period 2013-2017 with the Shannon Entropy-VIKOR model. The final energy consumption, GHG emissions, energy intention, the share of energy derived from renewable energy source, GDP are the indicators of the study. According to the analysis results, the performance rankings of the countries remained stable throughout the examined period. Nordic countries generally performed better compared to the Baltic countries. Latvia and Lithuania ranked last in the analyzed period. Sweden is ranked first, while Latvia and Lithuania are ranked last. According to the authors, the reason Nordic countries are ranked higher is because these countries are pioneers in renewable energy technologies and usage. In this study, the impact of renewable energy for the Nordic-Baltic countries during the 2020 period was measured using the entropy-PIV model. The study has created indicators such as "primary energy consumption, energy intensity, final energy consumption, share of energy from renewable sources, renewable energy source in transport, share of fossil fuels in final energy consumption, energy productivity, imports of solid fossil fuels by partner country, electricity prices for household consumers, GDP per capita." At the end of the study, similar to the work by [9], Nordic countries (excluding Finland) have shown better performance in terms of renewable energy development compared to the Baltic countries. Norway ranks first, while Finland and Lithuania are at the bottom. Finland's low ranking is attributed to its limited use of renewable energy in 2020, with only 10% of the country's electricity being generated by wind turbines. On the other hand, Norway's use of renewable energy for 98% of its electricity generation, Denmark producing half of its electricity from renewable sources, reaching its 2020 targets in 2012, Iceland's leadership in geothermal energy globally, and Sweden being one of the top users of renewable energy sources have all played a significant role in these countries' high rankings in renewable energy development.

On the other hand, it is frequently encountered in the literature that the entropy-PIV model is applied in real-life scenarios. [51] measured the sustainability performance of energy companies operating in Asia and Europe with entropy-PIV-ROV-GRA-MARCOS. [52] used the fuzzy AHP-entropy-PIV model to rank thirty-one carboxylic acids based on six different criteria. [53] used the entropy-PIV model in the preparation of a stable, low viscosity TiO2/EG-water nanocoolant. [54] preferred entropy-based WASPAS-PIV models in the external cylindrical grinding process of 65G steel. [55] used the equal weight-ROC-entropy-based PIV and TOPSIS model in difficult turning operations, and it was determined that the model was suitable. The final conclusion reached in these studies is that the model used is suitable for solving the problem addressed.

3.1. Sensitivity analysis

In this stage, a thorough sensitivity analysis was applied to verify the accuracy of the proposed model. Sensitivity analysis, which helps determine and manage uncertainties in data inputs such as sampling errors, measurement errors or missing data, enables obtaining more accurate and reliable predictions. This, in turn, leads to more informed decisions and enhances the reliability of the tool [56].

In the literature, sensitivity analysis can be carried out in various ways such as using different normalization techniques [56], varying different criteria weights ([57]; [58]; [59]), employing different MCDM methods ([59]) or altering the values in the algorithms of the methods ([60]). In this study, similar to the approach of [61], sensitivity analysis was conducted based on different criterion weights to test the ranking of alternatives obtained using the PIV method.

Sensitivity analysis of the results obtained with the proposed model is carried out for the following purposes: i) testing the robustness of results with variations in criterion weights, ii) determining the minimum percentage changes in weights that will alter the rank of any alternative and the best alternative, iii) identifying the most critical criterion that influences the alteration of rankings for both individual alternatives and the best alternative. In this regard, the impact of 34 different variations in weights (Table 7) on the results was examined.

The new criteria weight (W_i^*) is calculated using equation (1a).

$$\mathbf{W_i^* = |W_i \pm \delta|, \qquad 1 \le i \le n} \tag{1a}$$

W_i and δ represent the weight obtained with improved entropy and the weights indicated in Table 7.

The weight is normalized using equation (2a).

$$\mathbf{W_i'} = \frac{\mathbf{W_i^*}}{\sum \mathbf{W_i^*}}, \qquad \mathbf{1 \le i \le n} \tag{2a}$$

On the other hand, through the analysis, we determined the minimum percentage changes in the current weights of the criteria that influenced the ranking of alternatives. Additionally, we identified significant weights and critical decision criteria. After defining the minimum change, two fundamental terms can be used to measure and analyze the ranking. Equation (1b) defines the absolute change, while equation (2b) defines the relative change.

$$\boldsymbol{\delta_i'} = |\mathbf{W_i'} - \mathbf{W_i}| \tag{1b}$$

$$\boldsymbol{\delta_i''} = (\mathbf{W_i'} - \mathbf{W_i}) * \frac{\mathbf{100}}{\mathbf{W_i}}, \mathbf{for\ 1 \le i \le n} \tag{2b}$$

where δ_i', δ_i'', and n represent the changes in absolute term/in relative term and the number of criteria, respectively.

Table 6. Variations in weights.

δ(±0.01, ±0.05, ±0.1, ±0.125, ±0.15, ±0.175, ±0.2, ±0.225, ±0.25, ±0.275, ±0.3, ±0.325, ±0.35, ±0.375, ±0.4, ±0.425, ±0.45)

Source: [61]

Table 7. The effect of changes in weights on the ranking results.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	Ranking
w_i	0,0992	0,0930	0,1010	0,1017	0,0893	0,0963	0,0984	0,0994	0,0928	0,1290	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
δ	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	
0.01	0,0993	0,0936	0,1009	0,1015	0,0902	0,0966	0,0985	0,0994	0,0935	0,1264	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
-0.01	0,0991	0,0922	0,1012	0,1018	0,0881	0,0959	0,0982	0,0993	0,0920	0,1322	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
0.05	0,0995	0,0953	0,1007	0,1011	0,0928	0,0975	0,0989	0,0996	0,0952	0,1193	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
-0.05	0,0984	0,0860	0,1021	0,1033	0,0785	0,0926	0,0968	0,0987	0,0856	0,1580	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
0.1	0,0996	0,0965	0,1005	0,1008	0,0946	0,0981	0,0992	0,0997	0,0964	0,1145	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
-0.1	0,0129	0,1106	0,0164	0,0261	0,1692	0,0586	0,0254	0,0102	0,1132	0,4575	"$a_1>a_3>a_2>a_4>a_5>a_6>a_7>a_8$"
0.125	0,0996	0,0969	0,1005	0,1007	0,0952	0,0983	0,0993	0,0997	0,0968	0,1129	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
-0.125	0,1000	0,1241	0,0928	0,0905	0,1385	0,1113	0,1031	0,0994	0,1247	0,0156	"$a_1>a_3>a_2>a_8>a_6>a_5>a_4>a_7$"
0.15	0,0997	0,0972	0,1004	0,1007	0,0957	0,0985	0,0994	0,0997	0,0971	0,1116	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
-0.15	0,1016	0,1140	0,0979	0,0967	0,1215	0,1074	0,1032	0,1013	0,1144	0,0420	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
0.175	0,0997	0,0974	0,1004	0,1006	0,0961	0,0986	0,0994	0,0998	0,0974	0,1106	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
-0.175	0,1011	0,1094	0,0986	0,0978	0,1143	0,1050	0,1021	0,1009	0,1096	0,0613	"$a_1>a_3>a_8>a_2>a_5>a_6>a_4>a_7$"
0.2	0,0997	0,0977	0,1003	0,1006	0,0964	0,0988	0,0995	0,0998	0,0976	0,1097	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
-0.2	0,1008	0,1070	0,0990	0,0983	0,1107	0,1037	0,1016	0,1006	0,1072	0,0710	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
0.225	0,0997	0,0978	0,1003	0,1005	0,0967	0,0989	0,0995	0,0998	0,0978	0,1089	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
-0.225	0,1007	0,1056	0,0992	0,0987	0,1086	0,1030	0,1013	0,1005	0,1057	0,0768	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
0.25	0,0998	0,0980	0,1003	0,1005	0,0969	0,0989	0,0995	0,0998	0,0979	0,1083	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
-0.25	0,2463	0,0856	0,0788	0,0859	0,0730	0,0892	0,0740	0,0897	0,0709	0,1066	"$a_1>a_2>a_3>a_4>a_5>a_6>a_8>a_7$"
0.275	0,0998	0,0981	0,1003	0,1004	0,0971	0,0990	0,0996	0,0998	0,0981	0,1077	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
-0.275	0,1005	0,1040	0,0994	0,0991	0,1061	0,1021	0,1009	0,1004	0,1041	0,0834	"$a_1>a_3>a_2>a_5>a_6>a_8>a_4>a_7$"
0.3	0,0998	0,0982	0,1003	0,1004	0,0973	0,0991	0,0996	0,0998	0,0982	0,1073	"$a_3>a_1>a_2>a_5>a_6>a_7>a_8>a_4$"
-0.3	0,1004	0,1035	0,0995	0,0992	0,1054	0,1019	0,1008	0,1003	0,1036	0,0855	"$a_1>a_3>a_2>a_5>a_8>a_6>a_7>a_4$"
0.325	0,0998	0,0983	0,1002	0,1004	0,0975	0,0991	0,0996	0,0998	0,0983	0,1068	"$a_1>a_3>a_2>a_5>a_6>a_7>a_8>a_4$"
-0.325	0,1004	0,1031	0,0995	0,0993	0,1048	0,1017	0,1007	0,1003	0,1032	0,0871	"$a_1>a_3>a_2>a_5>a_6>a_8>a_7>a_4$"
0.35	0,0998	0,0984	0,1002	0,1004	0,0976	0,0992	0,0996	0,0999	0,0984	0,1064	"$a_1>a_3>a_2>a_5>a_6>a_7>a_8>a_4$"
-0.35	0,1003	0,1028	0,0996	0,0993	0,1043	0,1015	0,1006	0,1003	0,1029	0,0884	"$a_1>a_3>a_2>a_5>a_6>a_8>a_7>a_4$"
0.375	0,0998	0,0985	0,1002	0,1003	0,0977	0,0992	0,0997	0,0999	0,0985	0,1061	"$a_1>a_3>a_2>a_5>a_6>a_7>a_8>a_4$"
-0.375	0,1003	0,1026	0,0996	0,0994	0,1039	0,1014	0,1006	0,1002	0,1026	0,0894	"$a_1>a_3>a_2>a_5>a_6>a_8>a_7>a_4$"
0.4	0,0998	0,0986	0,1002	0,1003	0,0979	0,0993	0,0997	0,0999	0,0986	0,1058	"$a_1>a_3>a_2>a_5>a_6>a_7>a_8>a_4$"
-0.4	0,1003	0,1023	0,0997	0,0994	0,1036	0,1012	0,1005	0,1002	0,1024	0,0903	"$a_1>a_3>a_2>a_5>a_6>a_8>a_7>a_4$"
0.425	0,0998	0,0987	0,1002	0,1003	0,0980	0,0993	0,0997	0,0999	0,0986	0,1055	"$a_1>a_3>a_2>a_5>a_6>a_7>a_8>a_4$"
-0.425	0,1003	0,1022	0,0997	0,0995	0,1033	0,1011	0,1005	0,1002	0,1022	0,0911	"$a_1>a_3>a_2>a_5>a_6>a_7>a_8>a_4$"
0.45	0,0999	0,0987	0,1002	0,1003	0,0980	0,0993	0,0997	0,0999	0,0987	0,1053	"$a_1>a_3>a_2>a_5>a_6>a_7>a_8>a_4$"
-0.45	0,1002	0,1020	0,0997	0,0995	0,1031	0,1011	0,1005	0,1002	0,1021	0,0917	"$a_1>a_3>a_2>a_5>a_6>a_7>a_8>a_4$"

In Table 7, the values of w_i represent the weights obtained using the improved entropy method. The ranking obtained using the PIV method is $a_1 > a_3 > a_2 > a_5 > a_6 > a_8 > a_4 > a_7$. When examining the ranking results obtained under different variations, it has been determined that, except for the first three alternatives, the rankings of the other alternatives change when δ=-0.1. When δ is increased, the alternative in the first place (a_1) is changed under the condition $\delta = 0.3$.

As can also be seen from Fig. 2, the ranking remains the same up to scenario 6 (δ = 0.01-0.1). In scenario 18 (δ = -0.25), countries are increasingly arranged almost sequentially. Except for the rankings obtained from scenarios 6 and 18, it can be said that the other rankings are more compatible with each other. According to the analysis presented (Figure 2), it is observed that changes in the weight coefficient values of criteria mainly affect the ranking of alternatives a_4, a_7, and a_8. Alternatives a6, a_5, a_2, a_3, and a_1, on the other hand, are among the least sensitive alternatives in terms of ranking in the sensitivity analysis. For the weight factor δ [0.01, 0.275], alternative a_1 maintained its top position among the considered alternatives. However, for w ∈ [0.0992-0.1290]; there are significant changes in the ranking of alternative a_1. According to the analysis presented, the top-ranked alternative (a_1) remained dominant in almost all the 34 scenarios. It represents the best solution regardless of changes in the weighting coefficients of the evaluation criteria. Simultaneously, it was confirmed that alternatives a_4, a_7, and a_8 represent the worst solutions through all 34 scenarios.

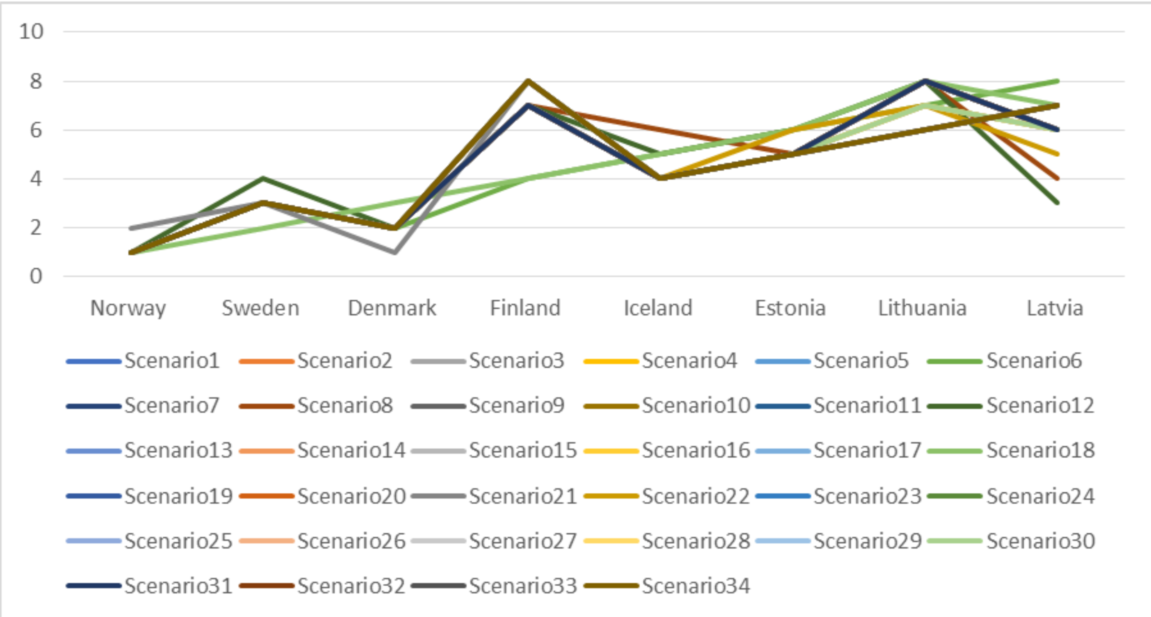

Figure 2. Rankings based on different weight sets.

According to [61], after defining the minimum changes, the analysis should be conducted in two steps. Firstly, the minimum change (relative top) that alters the ranking of the best alternative should be identified. Then the minimum change (relative any) in the weight of a criterion that changes the ranking of other alternatives should be determined.

3.1.1. Minimum weight change related to relative any and relative top alternative

The change caused by positive and negative variations in weights in the ranking of alternatives has been investigated using Eq. (1b). Accordingly, the minimum positive and negative changes that alter the ranking of alternatives are $\delta = 0.3$ and δ= -0.1, respectively. Under the $\delta = 0.3$ condition, the alternative in the first rank changes, while under the $\delta = -0.1$ condition, the ranking of alternatives a_4, a_5, a_6, a_7, and a_8 has changed.

Criterion c_2, as presented in Table 8, corresponds to the smallest relative weight change, amounting to 18.93%. Thus when the current weight decreases, criterion c_2 becomes the most critical factor responsible for altering the ranking of any alternative. Conversely, criterion c_8 corresponds to the smallest relative weight change, which is 0.402%. Thus when the current weight decreases, criterion c_8 becomes the most critical factor responsible for altering the ranking of any alternative.

Equation (3) was used to determine the minimum positive and negative changes that alter the ranking of the best alternative and to identify the most critical criterion. The results are presented in table 9.

Table 8. Evaluation of the most critical criteria for relative any alternative.

		c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
w_i		0,0992	0,0930	0,1010	0,1017	0,0893	0,0963	0,0984	0,0994	0,0928	0,1290
		c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
The minimum change in weight	$\delta = -0.1$	0,0129	0,1106	0,0164	0,0261	0,1692	0,0586	0,0254	0,0102	0,1132	0,4575
	$\delta = 0.3$	0,0998	0,0982	0,1003	0,1004	0,0973	0,0991	0,0996	0,0998	0,0982	0,1073
Relative change (%)		86,996	**18,925**	83,762	74,336	89,474	39,148	74,187	89,738	21,983	254,651
		0,605	5,591	0,693	1,278	8,959	2,908	1,220	**0,402**	5,819	16,822

Table 9. Evaluation of the most critical criteria for relative top alternative.

		c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
w_i		0,0992	0,0930	0,1010	0,1017	0,0893	0,0963	0,0984	0,0994	0,0928	0,1290
		c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
The minimum change in weight	$\delta = 0.3$	0,0998	0,0982	0,1003	0,1004	0,0973	0,0991	0,0996	0,0998	0,0982	0,1073
Relative change (%)		0,605	5,591	0,693	1,278	8,959	2,908	1,220	**0,402**	5,819	16,822

4. Conclusions

This paper determines an objective evaluation method for the renewable energy development in Nordic-Baltic countries. Our approach is based on ten indicators: "primary energy consumption, energy intensity, final energy consumption, share of energy from renewable sources, renewable energy source in transport, share of fossil fuels in final energy consumption, energy productivity, imports of solid fossil fuels by partner countries, electricity prices for household consumers, and GDP per capita". Eight alternatives such as Norway, Sweden, Denmark, Finland, Iceland, Estonia, Lithuania, and Latvia are considered. The methodology consists of three steps: (i) The improved entropy method is employed to weight the criteria, (ii) the PIV method is utilized to prioritize the alternatives, and (iii) sensitivity analysis is performed to test the robustness of the employed model.

Based on the improved entropy model, the criteria with the highest and lowest importance levels are c_{10} (GDP per capita) and c_5 (renewable energy source in transport), respectively. According to the PIV method, the ranking of countries concerning renewable energy development is as follows: Norway > Denmark > Sweden > Iceland > Estonia > Latvia > Finland > Lithuania. When decision matrices are examined, it is seen that Norway, Denmark, and Sweden are particularly advantageous in terms of benefit-oriented criteria. Reasons contributing to their development in the field of renewable energy include Norway's production of 98% of its electricity from renewable sources, most of the Denmark's electricity being generated from renewable energy, and Sweden's effective management of the wind energy market. In the Nordic-Baltic region, renewable energy development can be achieved by increasing the use of renewable resources, especially to produce electrical energy, increasing the installed power based on wind energy, and reducing greenhouse gas emissions.

To test the robustness of the model, 34 scenarios were established based on variations in weights. According to this, the minimum positive and negative changes in weights required for the current ranking to alter are δ = 0.3 and δ = -0.1, respectively. On the other hand, the minimum positive and negative changes that alter the order of any two alternatives in the current ranking are δ = 0.3 and δ = -0.1, and the smallest weight change required to alter the current ranking is 18.93%. The minimum positive change that alters the ranking of the best alternative is δ=0.3, and the smallest weight change required to alter the best alternative ranking is 0.402%. The most critical decision criterion is c_8 (imports of solid fossil fuels by partner country). Another noteworthy result is that when the weights decrease, the ranking of the best alternative remains unchanged. Due to the limited research on renewable energy development using MCDM methods, this study aims to fill this gap in the literature. The results of this study are considered significant for presenting the development of renewable energy in the Scandinavian-Baltic countries and proposing measures to policymakers and practitioners to

promote energy development. It is believed that the obtained results will benefit practitioners, and the proposed model can be easily applied in the field of renewable energy. Furthermore, the robustness of the model was tested by evaluating the impact of changes in criterion weights, and the minimum changes required in criterion weights to alter the ranking of alternatives were determined, identifying the most critical criterion influencing the changes in ranking. This situation provides an example for researchers to test different methods regarding how changes in criterion weights affect the results. In summary, Scandinavian countries have successfully achieved a high share of renewable energy, making renewable energy sources efficient and cost-effective projects, reducing dependence on fossil fuels, and increasing the share of hydroelectric energy in domestic production. In the Baltic countries, renewable energy sources such as onshore wind, solar, and hydroelectric power cover only a small portion of the total energy demand. The installation of wind turbines, the expansion of offshore wind turbine capacity, and the importance of the Baltic Sea in energy transformation should not be overlooked.
As a direction for future research, unlike this study, which is constrained by ten criteria, the number of criteria can be increased, and a comparison can be made between the results using new data. In the study, using only data from the year 2020 is another the limitations of the study. Addressing the same problem based on different periods may be useful in comparing the results. The renewable energy sector is of critical importance to all societies; therefore, the proposed framework can be applied to evaluate renewable energy development in other developing countries. The proposed sensitivity analysis approach in this study can be applied to a different MCDM method.

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