The analysis of the impact of news sentiment on the dynamics of energy resource imports and exports in Ukraine during the full-scale war

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Abstract

The context of this study is the use of news sentiment analysis to analyze the state of the energy sector in Ukraine during a full-scale war. The objective of the study is to use sentiment analysis based on the judgments of the large language model GPT-4 to determine the sentiment of news at different time intervals. The method used in the processing includes collecting data from a Ukrainian news site, pre-processing the data and applying the algorithms of the large language model to determine the sentiment level of the data. The results of the study include a set of news with assessed sentiment analysis, as well as visualization of the dependence of news sentiment on electricity imports and exports in Ukraine. The analysis of the results provides an understanding of the dependence of sentiment change compared to the previous months on electricity imports, as well as the trend of electricity imports in the face of constant negative news. The study concludes that the application of sentiment analysis together with visualization of data dependence in the energy sector is a valuable tool for determining the state of the energy sector and potential upward or downward trends. However, the sentiment analysis method used is expensive, and its application is relatively cheap on small amounts of data.

Keywords

Sentiment analysis, Ukraine war, GPT-4

1. Introduction

Until 2022, Ukraine played an important role in the European energy sector, both in terms of natural gas transit and for the export of electricity and other resources. However, with the outbreak of a full-scale war, Ukraine faced problems and challenges in the context of energy resources. With the onset of the so-called "carpet bombing" or "area bombing" [1], problems began in the field of electricity distribution, when missile attacks from Russia destroyed substations that distributed electricity between cities and regions. Over time, the attacks moved to electricity generation facilities such as thermal power plants, hydroelectric power plants and nuclear power plants. Despite all the difficulties, Ukraine tried to keep the energy sector operational and even provided electricity to neighboring countries for some time [2].

A significant factor in the resilience of the Ukrainian energy sector was the comprehensive support from the EU countries, which not only synchronized the energy system with Ukraine, but also provided equipment for the repair and installation of power generation and distribution

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facilities, which made it possible to promptly eliminate problems arising from massive missile attacks and drone strikes.

Against the backdrop of these geopolitical events, information has become as valuable a resource as physical resources. Any detail, any headline can provide insight into the overall picture of what is happening, as well as implicitly indicate the further course of events. News coverage in the media, such as reports of attacks on critical infrastructure facilities, or information on the provision of international assistance, helps assess the current situation and suggest potential developments, such as changes in the volume of electricity imports or exports. The tone and design of news can potentially influence the mood of both citizens and investors, representatives of the energy sector, the stock market and international relations [3].

During war, when uncertainty is high and quick decision-making is needed, understanding the impact of news sentiment on the energy sector becomes a matter of national and economic security.

This study will analyze how the media landscape affected the dynamics of Ukraine's energy imports and exports during a full-scale war. We use advanced natural language processing (NLP) techniques and quantify the emotional tone of media coverage related to energy trade and correlate it with changes in actual import/export volumes. This approach allows us to determine whether negative news accelerates crisis-induced market reactions or positive news, such as international support announcements, stabilizes trade activity.

The objective of the research is application of sentiment analysis to news related to energy topics using natural language processing techniques, as well as analysis conduction of the processed data in the form of displaying the dependencies of energy data on news sentiment.

2. Related Works

2.1. Sentiment analysis in the energy sector

The titled study "Sentiment Analysis of Investors and Consumers on Energy Market Based on BERT-BiLSTM" marks an important leap forward in NLP methods into energy markets [4]. It incorporates a mixed model of BERT-BiLSTM for the determination of sentiment in terms of investors and consumers within the energy market. The integration of BERT provides contextual understanding for textual data and BiLSTM incorporates the temporal dependency for better performance, forming the best framework for robust sentiment analysis. The result is an advanced and highly developed estimation and modeling system capable of sensing and inferring the market mood and attitude, which can prove essential for proper decision-making within any market context.

Another one study "EU Citizens' Twitter Discussions of the 2022–23 Energy Crisis: A Content and Sentiment Analysis on the Verge of a Daunting Winter" [5] explored an extensive analysis of Twitter discussion boards for the purpose of obtaining information on public sentiment and debate surrounding the energy crisis in the winter of 2022–2023. They utilized the appropriate keywords for all the EU and energy crisis-related terms to collect tweets written in six languages: German, Spanish, French, Italian, Polish, and English. They analyzed the networks to identify the influential users, while the sentiment analysis allowed them to assess the mood of the public. The findings highlighted that all languages have a dominance of negative sentiments represented by fear and sadness. The discussion topics mostly revolved around the growing energy prices and political events. Public discourse was marked by widespread concern about the energy crisis getting worse [5].

The research presented demonstrates how social media such as Twitter could be a good tool for instant sentiment analysis, particularly during emergencies. Sentiment analysis gathers public opinions and hot topics of discussions so that the analysis can provide information to policymakers and other relevant stakeholders, leading to faster and better-targeted intervention. The methodology and insights contained in this research would, however, better assist the understanding of how the attitude towards news may shape the import and export of energy, specifically within conflict zones like Ukraine. Such a methodology is able to provide a more effective approach toward predicting energy trade changes during times of geopolitical conflict with such analyses embedded within their respective economic models.

2.2. News sentiment as a predictor of energy trade dynamics

The study "Opinion Mining of Green Energy Sentiment: A Russia-Ukraine Conflict Analysis" [6] analyzed how public sentiment toward green energy was altered by the outbreak of the Russia-Ukraine war. Using Twitter data from 16 February to 3 March 2022, the authors monitored sentiment change before and after the actual conflict escalated. Based on the analysis conducted using the NRC lexicon, their analysis revealed that the predominant feelings before the war were changing: whereas in the pre-war period, mainly positive sentiments were present, after the invasion, there arose feelings such as disgust, fear, and sadness. Nevertheless, an uptick in trust revealed that despite the fears, the population had come to realize the need for resilient energy infrastructure.

The findings of this study reveal that a spike in negative sentiment might influence the acceptability of certain policies and stability of energy markets, yet trust in green energy could maintain the long-term interest, despite the short-term pessimism [6]. These observations provide a basis for analyzing the extent to which news sentiment can affect the dynamics of energy trade during the ongoing full-scale war against Ukraine, thereby highlighting the need for integrating sentiment analysis in energy market studies.

2.3. News sentiment as a predictor in other fields

The analysis of how media influence the development of energy resource trades between Ukraine in the context of full-scale war necessitates the identification of appropriate ways to interpret sentiment analysis outcomes. In this respect, the article "Visualizing Sentiment Analysis Results on Social Media Texts" [7] suggests two original ways to improve the interpretability of sentiment analysis results through visualization techniques.

In this research the technology called VADER (Valence Aware Dictionary for Sentiment Reasoning) is employed in performing the sentiment analysis on datasets taken from the social networking platforms of Twitter, Facebook, and Reddit. VADER produces heatmaps that visually represent sentiment scores and allow the user to gain some instant understanding of the data being analyzed. This approach is capable of capturing the wider aspect of the sentiment landscape necessary for an accurate measurement of public opinion and how this opinion can affect the dynamic of energy import and export during geopolitical conflicts [7].

The study “Financial Sentiment Analysis: Techniques and Applications” [8] presents a general overview of the methodologies and the area of their application in the financial world. The paper examines the methodologies used in financial sentiment analysis: NLP techniques include, but are not limited to, lexicon-based approaches and machine learning models. The main idea of these methodologies is to extract the attitude embedded in different textual sources, such as news articles, social media posts, and financial reports. The extracted sentiments are further employed in stock price prediction, risk management, and market trend analysis. When sentiment analysis enters into the financial model, stakeholders obtain more insight into the market itself, which could also gain relevance with regard to the influence of news sentiment on energy trade under the impact of geopolitical shocks [8].

3. Methods and Materials

3.1. News sentiment analysis: data extraction

The data extraction process will serve as the foundation for analyzing the sentiment of news articles related to energy resource imports and exports. The UML activity diagram, as illustrated in the Figure 1, consists of multiple steps, starting from collecting relevant news data (Step 1), exporting it for processing, and preparing it for sentiment analysis.

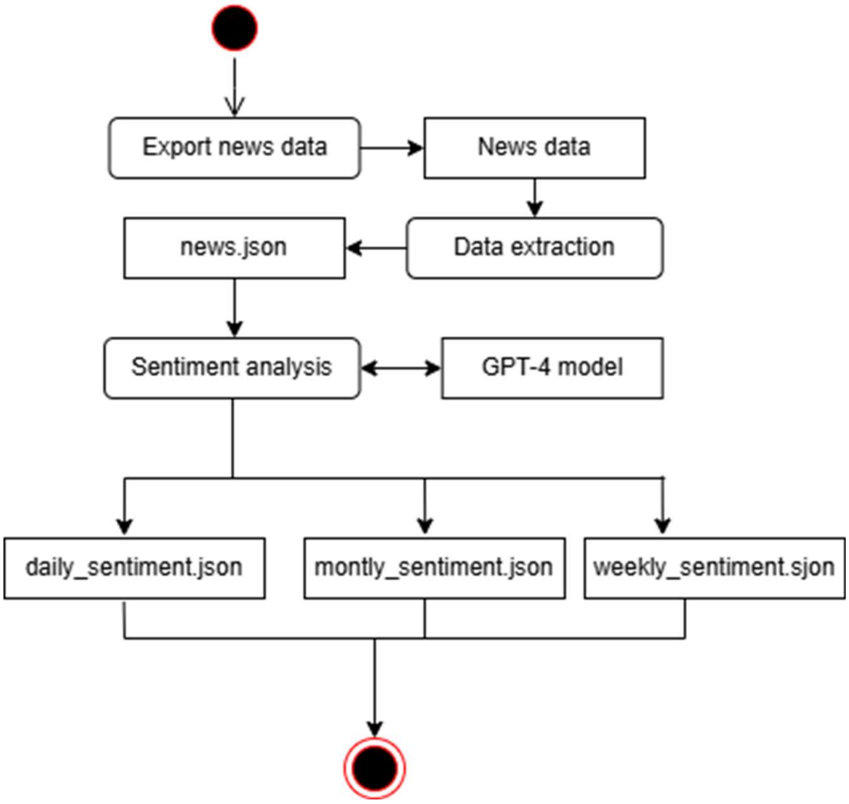


Figure 1: The UML activity diagram of Data Extraction workflow.

The process will begin with retrieving news data (Step 1) from online sources. To extract relevant articles, a web scraping approach will be used, employing "requests" to fetch web pages and "BeautifulSoup" to parse their HTML content [9]. The scraper will scan articles for energy-related keywords, such as "power plant", "blackout", "electricity supply" etc., ensuring that only relevant news is selected. Once relevant articles are identified, they will be structured and exported to a Python-based data extraction module (Step 2). This script will extract key information such as the title of the news article, its text content, and the publication date. The extracted data will be stored as a structured JSON file, "news.json" (Step 5), which will serve as the primary input for sentiment analysis.

The extracted news data will then be processed for sentiment analysis. The JSON file (Step 6) will be loaded into a processing script where text preprocessing steps will be applied, including date conversion to ensure correct time-based analysis, keyword weight assignment to refine sentiment impact, and normalization of sentiment values to maintain consistency in further aggregation. A Python-based sentiment analysis model (Step 7) will process the structured text data, utilizing natural language processing (NLP) techniques and sentiment scoring algorithms to determine the sentiment polarity of each news article.

To enhance the accuracy of sentiment interpretation, GPT-4 (Step 8) will be integrated into the analysis process. This AI model will refine sentiment classification by providing deeper contextual analysis, improving polarity detection, sentiment trend forecasting, and energy sector-specific sentiment adjustments.

To analyze sentiment trends over time, the data will be aggregated into different time periods, including daily, weekly, and monthly sentiment scores. These aggregated sentiment files (Step 9) will be stored in "daily_sentiment.json", "weekly_sentiment.json", and "monthly_sentiment.json", ensuring that sentiment scores reflect trends at different temporal scales. This structured extraction and processing pipeline will ensure that the sentiment analysis phase receives high-quality, pre-processed input, enabling more accurate and meaningful insights into energy-related news trends.

3.2. Analysis of sentiment impact on electricity data

Sentiment analysis scores will be incorporated into the electric power import and export statistics to analyze the relationship between news sentiment and electricity trade. This work will entail data merging, statistical correlation analysis, linear regression modeling, and topic modeling to understand patterns and relationships. The Figure 2 represents the data analysis and visualization workflow.

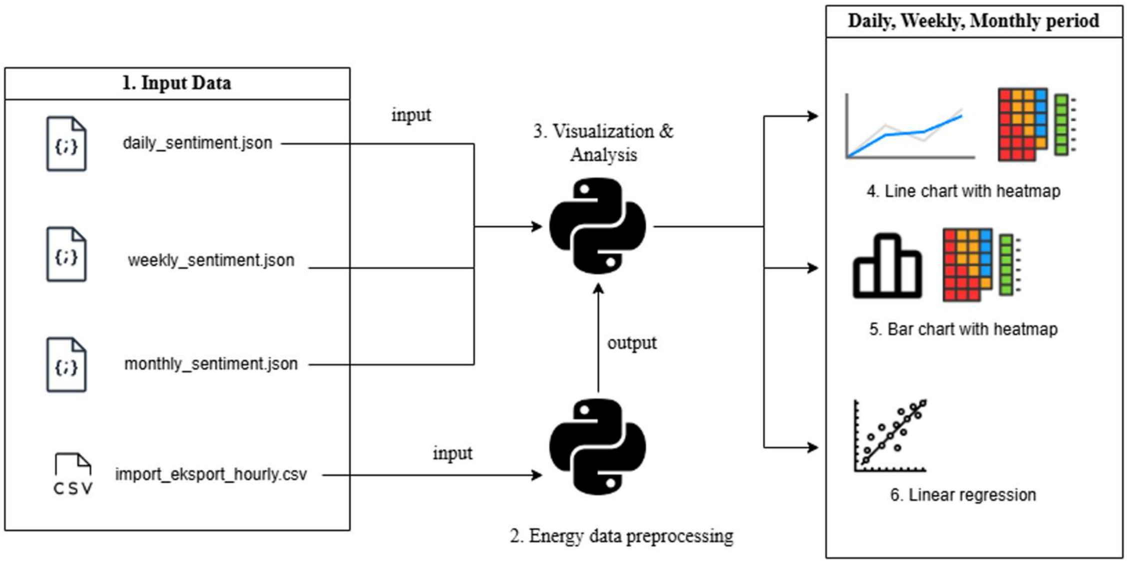


Figure 2: Data analysis and visualization workflow.

Sentiment data will first be merged with electricity data, while weekly and monthly aggregated sentiment scores are correlated with the electricity import/export data. The data sets will be paired through timestamps to ensure that the trends in sentiment align with the trends of energy import/export over time. Then, the "Sentiment change rate" will establish the link of such a change to the variation in energy flow. Correlation analysis based on Pearson coefficient will be performed to assess the ways sentiment has had an effect on electricity data [10]. Pearson correlation will quantify how much "Sentiment trends" aligns linearly with "Electricity trade changes" [10].

The models will also quantify how changes in sentiment scores affect "Electricity import/export variations" with time using linear regression modeling. This relationship strength and direction will be established based on the size and sign of the regression coefficients. Besides sentiment analysis, topic modeling will identify main themes in the news articles and explore the relation of such themes to "Sentiment scores" and "Electricity trade dynamics".

Dominant themes related to energy-related news will be assessed using Latent Dirichlet Allocation (LDA), which will analyze their effects on sentiment [11]. This method will help understand whether specific narratives (e.g. energy crises, infrastructure attacks, political decisions) are linked with fluctuations in electricity imports and exports. Besides visualization of "Electricity import/export values" combined with "Sentiment change" data by means of "Heatmaps", we will also display scatter plots with regression lines that plot "Sentiment scores" against "Energy flow changes".

The conjunction of sentiment analysis, linear regression, and topic modeling will offer an all-embracing view of whether news sentiment could serve as an important factor affecting the electricity trade changes, further providing insight into how it might function as a predictive indicator in the context of geopolitical instability.

3.3. GPT-4 in news sentiment analysis

The application of GPT-4 for the sentiment analysis of texts in news articles has several cons compared to the other natural language processing (NLP) methodologies. It does not employ lexicon-based methods or simple machine learning models. It is a deep contextual approach which considers the slight mood shifts, irony, sarcasm, and other implied meanings present in news texts. GPT-4 can also be trained in certain fields for use in certain contexts, therefore it would definitely prove helpful in the energy sector in the light of the ongoing news [12].

Another advantage of GPT-4 is that it understands a more nuanced level of sentiment rather than the more simplistic polarity classification (positive, negative, neutral). It would not rely simply on sentiment dictionaries, allowing the user the ability to reason about context-based conclusions, based on historical trends, and geopolitical considerations. This would make a human-like justification for the sentiment, increasing transparency and interpretability in the sense of sentiment analysis. It is possible also to integrate multilingual features if a person intends to investigate other media outlets in different languages in order to conduct a fairer analysis with respect to various types of news writing [12].

The model-based algorithm has certain restrictions. For instance, one can hardly deal with massive amounts of data for which expensive searches become necessary when one compares to traditional sentiment analysis models. Further, its processing speed is significantly lower than that of pre-trained sentiment classifiers, making it inadequate for sentiment analysis of real-time data or at high frequencies. Also, GPT-4 is like a black box: it would not give any insight about how it came to the decision it had made, which complicates systematic reorganizing or fine-tuning of results. GPT-4 has some bias in classification: hence, even in highly accurate political-sensitive cases, it would have a tendency to favor certain aspects [12].

The work currently utilizes GPT-4 on a limited basis, within the scope of pilot projects involving only small datasets. It will afford insights into the ability of GPT-4 for sentiment analysis while, at the same time, initiating a debate on scalability challenges faced with larger datasets. Considering the enormous cost associated with GPT-4 for big data in large-scale extensive sentiment extraction, it may turn out to be impractical to conduct analyses of large-scale datasets with GPT-4. Therefore, although GPT-4 has demonstrated great capability in the mood of energy-oriented news, larger-scale deployment will require further NLP models or hybrid systems.

4. Experiment

4.1. Data collection process

Based on [9], this work adopted a data collection methodology that was established before. It consists of two parts: extracting news articles from the web [13] on energy-related keywords and structuring them for further sentiment analysis. The predetermined set of keywords on Figure 3 was used to ensure that the news articles obtained in data collection are relevant.

```
KEYWORDS = [
    'power plant', 'thermal power', 'hydropower', 'nuclear power',
    'transformer', 'substation', 'electricity', 'reactor', 'turbine', 'generator',
    'power outage', 'load shedding', 'energy crisis',
    'blackout', 'power failure', 'electricity supply', 'power restoration', 'electrical disruption',
    'power cut', 'energy blackout', 'grid failure', 'electric service', 'power interruption',
    'no light', 'without electricity', 'power loss', 'no power', 'lights out', 'electricity down',
    'electric'
]
```

Figure 3: The list of selected keywords for news data extraction.

The keywords consist of such related terms as power infrastructure, electricity generation, energy supply, and disruption. This was in order to extract news articles on the energy crisis, power cut outages, destruction of important infrastructure, and electricity issues triggered by geopolitical events. These keywords were chosen in order to capture a wide array of topics on energy in the news. They range from technical terms like "turbine" and "reactor" to broader crisis-related terms such as "blackout," "grid failure," and "no power" so as to broaden the scope of coverage of news articles dealing with supply of electricity and disruptions. In the framework of the context provided by the Russia-Ukraine war, those keywords will allow tracing the power outages triggered by attacks on the energy infrastructure, emergency power restoration efforts, and fluctuation of electricity supply and trade. The Figure 4 represents the preview of extracted news.


```
[
    {
        "title": "Russian missiles hit one of DTEK’s thermal power plants on New Year’s Eve",
        "text": "One of the thermal power plants of the DTEK company has been damaged as a result of another Russian missile
        attack on New Year’s Eve.\n\n\nDTEK company also adds that this is the 23rd terrorist attack of the Russian Federation
        during which the company’s equipment has been damaged.\n\nVolodymyr Kudrytskyi, CEO of Ukrenergo National Energy Company,
        said that theoretically there is a possibility of a complete blackout, but in practice he does not see such a danger now.",
        "date": "2023-01-01"
    },
    {
        "title": "Ukraine’s national electricity company assesses probability of another blackout",
        "text": "The head of National Energy Company of Ukraine Ukrenergo, Volodymyr Kudrytskyi, said that there is a possibility
        of a complete blackout, but in practice he does not see such a danger now.\nThis was reported by Volodymyr Kudrytskyi on
        air during the 24/7 national joint newscast.\nAnswering the question whether a total blackout is possible in Ukraine,
        Kudrytskyi said that there is such a threat in theory, but in practice he does not see such a danger right now.\n\"I
        believe that we have already passed the worst with the missile attacks, I really hope so. The dynamics of these attacks
        and the effect of those attacks show that the Russians have less and less ability to cause any disturbances in our energy
        system,\" added Kudrytskyi.\nHe also noted that energy workers have also grown accustomed to the new missile attacks by
        the terrorist state on our energy system. Therefore, Russian troops can demonstrate little new on the battlefield against
        the Ukrainian energy system.\n\n\nAs a result of preventive technical measures and the excellent work of the Air Defense
        Forces, Ukraine's energy system was not seriously damaged after another missile attack by the terrorist state on Saturday,
        31 December.",
        "date": "2023-01-01"
    },
    {
        "title": "Occupiers leave Kherson without electricity on New Year’s Eve",
        "text": "Kherson and neighbouring settlements were left without electricity from Russian attacks on New Year’s Eve.\n\n\n
        Ruscists targeted and hit a critical infrastructure facility. The downtown area and KBK district [of Kherson - ed.],
        Bilozerka, Komyshany and other villages are cut off from the power grid.\"",
        "date": "2023-01-01"
    },
```


Figure 4: Sample of News Articles from “news.json” file.

The news articles were extracted from January 2023 to January 2025. Such time periods were selected in order to capture two whole years of data, during ongoing Russia-Ukraine war. It would be able to include seasonal trends, electricity trade flux, and the major geopolitical events influencing energy supply. January 2023 was chosen as a starting point since that marked the escalation of attacks against Ukraine's energy infrastructure at the end of 2022 [1-2], and it had a considerable effect on electricity import and export. With the January 2025 date included, the longer trends and the policy shift in the energy trade could also be analyzed. It was also by considering this two-year period that the dataset was able to cover how geopolitical instabilities have influenced energy supply and provided sufficient observations for sentiment analysis and statistical modeling of electricity trade fluxes.

For the study, the Ukrainian news website 'Ukrainska Pravda' was selected [13]. This resource, as a news portal, covers a wide range of events – from military conflicts, including combat operations and shelling, to political, social and economic processes in Ukraine and beyond. The information on electricity imports and exports represented on Figure 5 was collected from Energy Map under the heading “Hourly electricity imports and exports” dataset [14]. Energy Map is a public open data platform containing live and historical energy information regarding generation, consumption, and trade crossing the border. It collects data from many national grid operators to allow for the highest degree of accuracy and transparency possible. This particular dataset is composed of hourly import/export records that can provide a comprehensive evaluation of fluctuations in electricity trade along with the correlation with the time course of news sentiment dynamics [14].

```
2024-02-14,16:00:00-17:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Poland,0.0
2024-02-14,17:00:00-18:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Poland,0.0
2024-02-14,18:00:00-19:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Poland,0.0
2024-02-14,19:00:00-20:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Poland,0.0
2024-02-14,20:00:00-21:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Poland,0.0
2024-02-14,21:00:00-22:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Poland,70.0
2024-02-14,22:00:00-23:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Poland,70.0
2024-02-14,23:00:00-00:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Poland,0.0
2024-02-14,00:00:00-01:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Romania,70.0
2024-02-14,01:00:00-02:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Romania,50.0
2024-02-14,02:00:00-03:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Romania,50.0
2024-02-14,03:00:00-04:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Romania,50.0
2024-02-14,04:00:00-05:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Romania,50.0
2024-02-14,05:00:00-06:00:00,IPS of Ukraine (synchronized with ENTSO-E systems),export,Romania,35.0
```

Figure 5: Sample of "Hourly electricity imports and exports" dataset.

4.2. Sentiment analysis

The sentiment analysis started from extracting sentiment scores of the articles using GPT-4 LLM. Sentiment scores were analyzed through prompt-based techniques whereby GPT-4 would provide an assigned score between -1 and 1, negative to positive based on the content of text. Such a way made classification into sentiment easier, in context-based manner, than general lexicon. For the interpretation of sentiments to be as accurate as possible, a keyword weighting technique has been devised. In addition to sentiment classification, GPT-4 was also employed to assign weighting coefficients to each article. Using its internal algorithms and language understanding capabilities, GPT-4 identified the presence and relevance of energy-related keywords within the text. The weight for a particular news article depends on the number of energy-related keywords contained in it. The total number of such keywords acts as a multiplier for the obtained sentiment score. This weighting ensures that articles that had a higher share of energy-related terms would have an important influence on the results of sentiment analysis.

The program assigns weighted scores based on the sentiment expressed by an article and on its content. A sentiment score is a rating assigned to an article according to content and energy-related words found in it. An example would be an S score, calculated as follows:

$$S = s * k, \tag{1}$$

where s is the sentiment score assigned by GPT-4 and k is the number of energy-related keywords found in the article.

Since the dataset was dominated by negative news articles, which skewed the overall sentiment distribution, an adjustment was applied to increase the weight of positive sentiment values. This correction was implemented using the following transformation:

$$S_a = S * 2.5, \qquad S > 0, \tag{2}$$

where S is a weighted score.

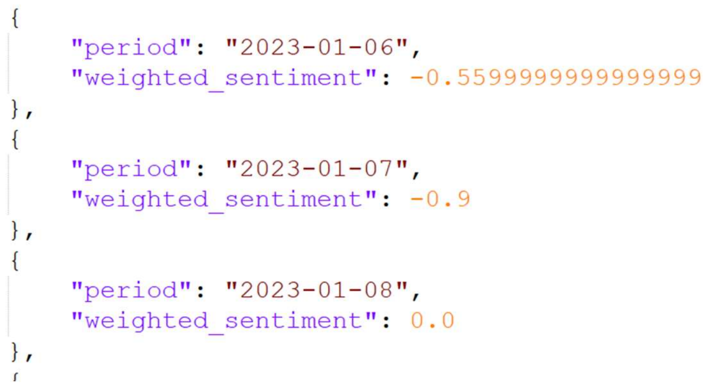
This adjustment is aimed at equalizing the representation of sentiment to guarantee that positive news would not be downgraded in the combined results. Otherwise, the result would suggest that there was no variation during that period: there will be negative feeling throughout the duration, which is not really the case, as the energy sector was able to restart operations and implement policy interventions to ensure energy supply and a positive contribution to the energy market.

After calculating the sentiment scores for individual articles, the results were aggregated over different time periods:

$$S_p = \frac{\sum S_a}{N}, \tag{3}$$

where S_p is the daily, weekly, or monthly weighted sentiment, S_a is the adjusted score and N is the total number of articles in the specific period.

Final aggregated sentiment values were stored in structured JSON files (daily_sentiment.json, weekly_sentiment.json, monthly_sentiment.json, quarterly_sentiment.json) for further correlation analysis with electricity import/export data. The sample data is represented on Positive sentiment weights were weighed, which had a strong impact on the analysis, so as to prevent over-representation of negative sentiment within the results. But even after this correction, overall tendency remained negative in nature, reflecting the unstable energy sector in view of ongoing geopolitical conflicts.



```
{
    "period": "2023-01-06",
    "weighted_sentiment": -0.5599999999999999
},
{
    "period": "2023-01-07",
    "weighted_sentiment": -0.9
},
{
    "period": "2023-01-08",
    "weighted_sentiment": 0.0
},
```


Figure 6: The data preview of “daily_sentiment” JSON file

4.3. Visualization of sentiment analysis results

Daily and weekly visualizations were conducted of the results from the initial sentiment analyses based on daily and weekly sentiment scores that were overlaid with electricity import and export data. However, the results indicated that daily and weekly period did not reveal anything meaningful, as time intervals were far too short to see major shifts in electricity trade after news releases, as it is represented on the Figure 7. Short-term variations in trends for sentiments made it challenging to identify clear trends or correlations with volumes of electricity import/export. Because of this, analysis and visualization were eventually performed only at the monthly level, with more stable trends of sentiments being able to offer a clearer perspective of possible effects on electricity trade.

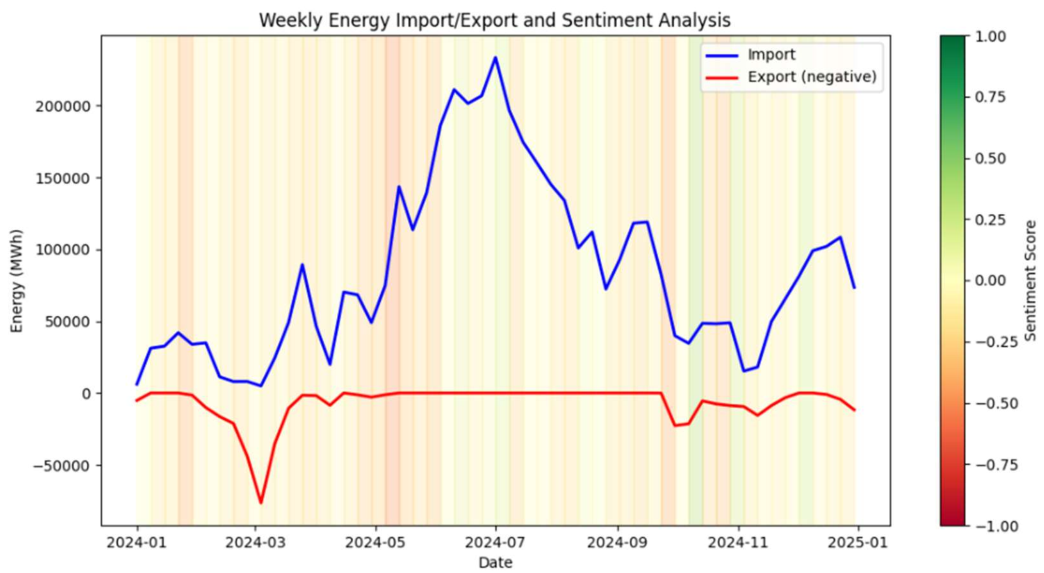


Figure 7: Line chart of daily import and export volume change with the weekly coloring based on sentiment score heatmap.

Electricity trading was largely impeded due to the major problem that there was a lack of time lag between news sentiment changes and its possible effect. Sentiment numbers are shifted backwards by a month, as there is never an automatic change of sentiment on imports and exports in energy trades, thus establishing correlation with trade movement. This adjustment allowed better examination of the previous month's sentiment change effects on electricity import/export volumes in the current month [15]. Also, the change in sentiment was calculated against the past months, not the absolute values of sentiment. This was done in order to enable an understanding of the direction of trends instead of the magnitude of sentiment. With this method, the analysis could get a better idea about the ways changing sentiment dynamic would influence electricity trade with time. In the last part of the analysis, the information on electricity trade was represented in a more visual manner: through the monthly sentiment heatmaps and scatter plots with regression lines, the color-coded background was used to show the trends and changes in sentiment flows. This was much better in terms of reducing noise introduced by short-term volatility of sentiment to the extent that it relates news sentiment with electricity trade.

The implemented line chart displays monthly sentiment shading that illustrates electricity imports and exports with the corresponding news sentiment trends over time. Time is on the x-axis, electricity trade volume is plotted on the y-axis, and imports and exports are plotted separately: as exports were negative values, they fell below the baseline. Each month was assigned a sentiment score to determine its background color. Red means lower sentiment than the previous month, blue means higher sentiment, and muted tones for neutral months. Instead of shading based on the overall sentiment score, this visualization emphasizes the sentiment change dynamics, making it easier to recognize the periods of substantial shifts in public opinion. It has been divided into monthly categories with specific color coding for each part of the time period, providing transparency in the analysis of possible relationships between changes in market sentiment and energy market dynamics.

Apart from visualization of line chart, energy-related news articles were analyzed using Latent Dirichlet Allocation (LDA) to visualize key topics related to the modeling and visualization of sentiment. Stop words and unrelated words were removed from the dataset so that only relevant words could be taken into consideration during the extraction of topics. A bag-of-words approach was used where vocabulary size was restricted to 500 words. These words corresponded to the words most frequently encountered in the dataset for better efficiency in modeling. The number of topics was set to five, balancing interpretability and topic granularity. Each article was assigned to one of these topics after the training of the model, and the identified theme related to its corresponding sentiment score. Bar charts, which displayed the topics' position on the x-axis and their absolute sentiment values on the y-axis, visualized the distribution of the sentiment per topic. Coloring with a color gradient separated highly polarized topics from the ones showing more balanced distributions of sentiment, which allowed easier explanation of the way in which different news topics had influenced changes in sentiment over time.

For the linear regression between electricity import/export volumes and the score for sentiments, data aggregation was done for one month at a time to account for the trend and smooth out the noise. Sentiment scores for months ahead were used, so a time lag adjustment of the one month was done to permit the model to capture the influence of the previous month's sentiment upon current electricity trade behavior. The dependent variables were import volume change and export volume change, while the independent variable was the weighted previous-month sentiment score. Both Pearson and Spearman correlation coefficients were calculated for the evaluation of the strength and nature of the relationships established. The regression outcomes were displayed with scatter plots of data points and fitted trend lines, where the previous month's sentiment score is along the x-axis and the change in electricity trade volume is plotted on the y-axis. The technique allowed for the pattern to be inferred on how the shifts in energy-related news sentiment had an impact on electricity imports and exports.

5. Results

5.1. Line chart analysis

The line chart on the Figure 8 provides the daily import and export volume of electricity over time. Background shading shows monthly changes in sentiment. The shading of colors reflects changes in sentiment: red signifies a decrease in sentiment from the previous month, while blue indicates improvement in sentiment. The time axis runs from January 2023 to January 2025, while the volume of electricity traded along the y-axis is in MWh, the import volumes in blue and export volumes in red are shown.

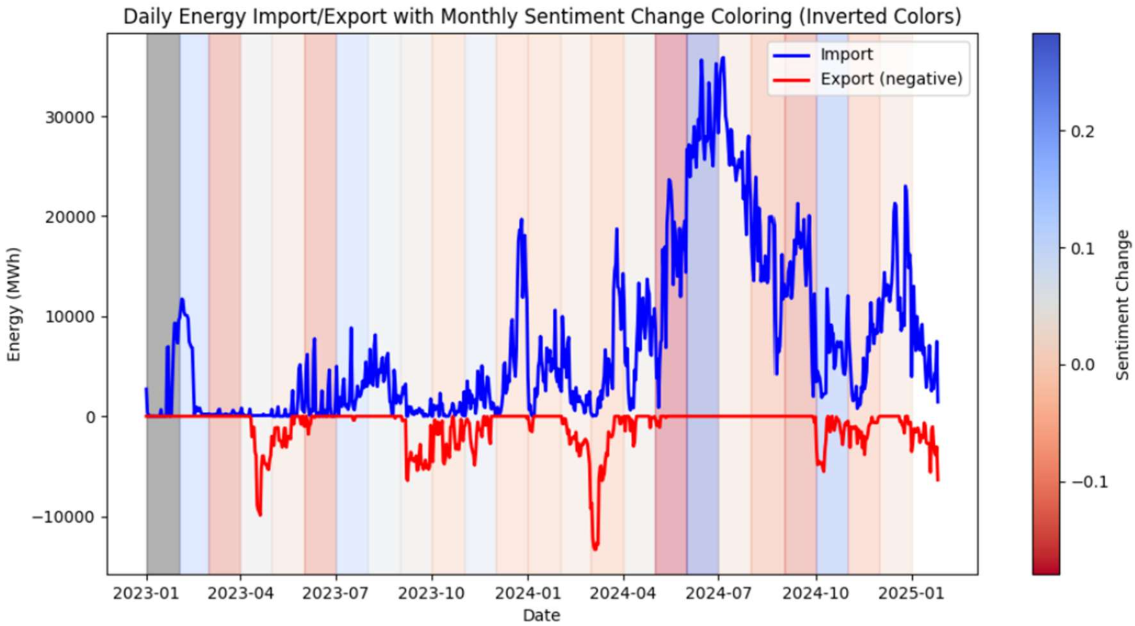


Figure 8: Line chart of daily import and export volume change with the monthly coloring based on sentiment score heatmap.

The main observation made on the graph is that prolonged periods of slightly negative sentiment changes tend to correlate with a steady increase in electricity imports.

This pattern suggests that when sentiment remains consistently negative but without drastic shifts, demand for imported electricity is likely to grow over time. Conversely, significant sentiment drops appear to have a stronger and immediate impact on electricity imports, as seen in June 2024, where a sharp sentiment decline resulted in a spike in electricity imports, reaching one of the highest recorded peaks. This fact suggests that sudden changes in public sentiment can act as short-term triggers for increased electricity demand, often driven by news of infrastructure damage, energy crises or supply instability. This fact suggests that sudden changes in public sentiment can act as short-term triggers for increased electricity demand, often driven by news of infrastructure damage, energy crises or supply instability.

In July 2024, the highest point for imports is reached, with a great amount of undulating after that. For some, sentiment changes were quite high with a negative sentiment alternating with a positive sentiment for some months. One conclusion to be drawn is that large sentiment variations represent one of the indicators for instability in the volumes imported; perhaps this instability of the external shocks and market uncertainty is affecting energy trade. Another point to note is that the export volumes were already decreasing from their peak, but to a small degree, they always showed some variation. This means that whereas import dependency reacts sharply to sentiment variations, exports remain little-affected by fast and short-lived sentiment changes. One possible reason could be that import decisions seem to be more responsive to sentiments brought about by a crisis, while stability in exports can be explained through long-term contracts or planned energy supply.

Basically, after July 2024, fast sentiment changes bring an unpredictability in trends in the electricity import, whereas the changes in export are far less affected by the sentiment shifts that come and go in no time. Therefore, further study is required to understand sentiment variability that spans over several months to identify the overall impacts it would carry in electricity trade.

5.2. Bar chart and topic analysis

The Table 1 presents the five topics extracted using Latent Dirichlet Allocation (LDA), each represented by five most relevant keywords, while the bar chart on the Figure 9 visualizes the absolute sentiment scores for each of these topics. The x-axis of the bar chart represents the topics, and the y-axis shows the absolute sentiment intensity, with a color gradient indicating sentiment polarity—red for negative sentiment and blue for more neutral or positive sentiment. Analysis of these topics reveals patterns in news articles, demonstrating how sentiment changes depending on the type of news coverage.

Table 1
Topic modeling results

Topic number	Keyword 1	Keyword 2	Keyword 3	Keyword 4	Keyword 5
Topic 1	attack	forces	energy	reported	war
Topic 2	plant	power	nuclear	Kakhovka	water
Topic 3	defense	war	president	reported	said
Topic 4	power	electricity	energy	supply	consumers
Topic 5	energy	support	million	company	European

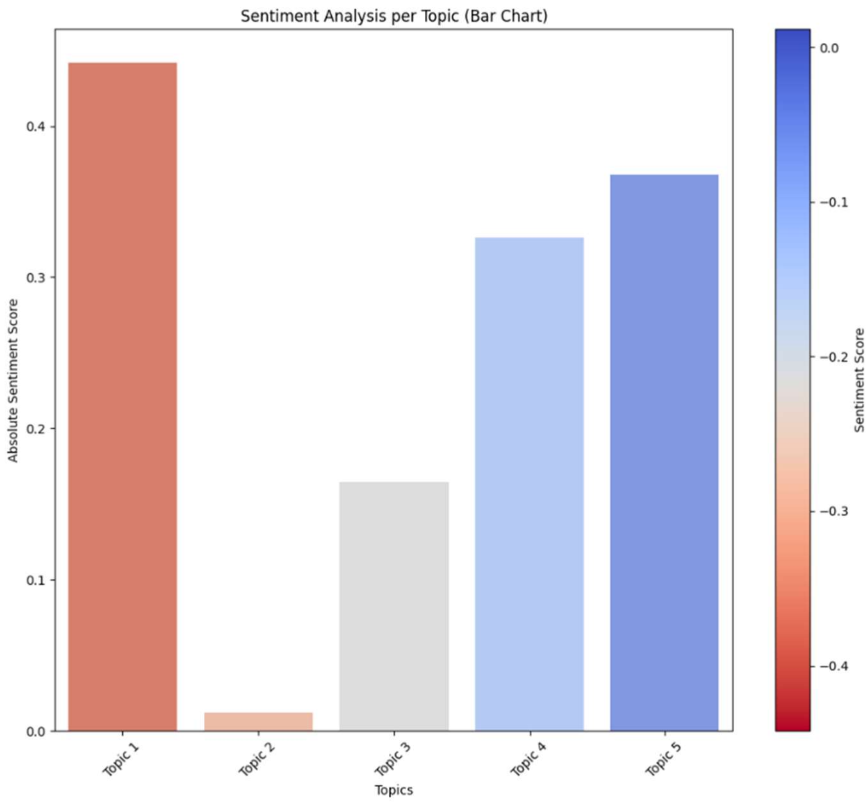


Figure 9: The bar chart of absolute sentiment scores for each of these topics with the sentiment score coloring.

It is most likely, that “Topic 1” speaks about news about the attacks of missiles on critical energy structures, given the presence of the keywords: “attack”, “forces”, “reported”, and “war”. This one is given the absolute highest sentiment score, as it involves emotionally charged materials-mostly due to the extent of damage to energy systems and to public safety.

The “Topic 2” contains various vocabulary to express “energy” issues: “plant”, “power”, “nuclear”, and “Kakhovka”. However, this mix of keywords does not provide clarity on whether these articles focus on infrastructure damage, policy discussions, or operational issues. In other words, in absolute terms, the low sentiment score suggests that these are factual, neutral news items with little negative emotional coloring.

“Topic 3”, however, comprises some discussions revolving around political and defense issues, including words like “defense”, “war”, “president”, and “reported”. This may mean that the news stories in this Topic may be less directly relevant to energy-related issues but were included in the dataset as a by-product of keyword filtering during data collection. The absolute sentiment score here is moderate, signifying that although the articles discuss geopolitical events, they are much less emotional than those from Topic 1.

”Topic 4” is likely associated with news about electricity supply, energy distribution, and consumer-related energy issues, as indicated by keywords such as “power”, “electricity”, “energy”, “supply” and “consumers”. The sentiment score for this topic is moderately high but leans toward the positive range, as shown by its blue shading in the bar chart. This suggests that articles within this topic contain a mix of neutral and slightly positive sentiments, likely due to discussions on energy stability, supply restoration, and infrastructure improvements rather than crisis-related disruptions. Compared to more emotionally charged topics like “Topic 1” (attack on infrastructure), “Topic 4” appears to include news that provides updates on energy availability and solutions rather than crisis narratives. The presence of the word "consumers" further suggests that some articles in this category might discuss government policies, energy pricing, or efforts to stabilize electricity distribution for the public, contributing to its relatively balanced sentiment profile.

“Topic 5” appears to focus on news related to international energy support and financial aid, as reflected by words like “energy”, “support”, “million”, “company”, and “European”. The sentiment in this topic leans toward a more neutral or slightly positive range, as news about financial assistance and energy supply initiatives may contribute to stability and reassurance in the energy sector.

Overall, there is strong evidence in “Topic 1” that reflects war-based strikes aimed at energy infrastructures. While topics 2 and 5 express less emotional polarity, this may be a function of their focus on policy, economics, and energy system-related debates. “Topic 3” injects some noise into the dataset, which indicates that some non-energy-related political news articles may have slipped in due to keyword duplication. These results demonstrate the value of contextual filtering in analyzing energy-related news, which would greatly improve the precision of the topic modeling used in them.

5.3. Linear regression analysis

The scatter plots on Figure 10 with regression lines illustrate the relationship between the previous month's sentiment score and changes in electricity import and export volumes. The left plot represents the correlation between sentiment and import volume change, while the right plot shows the correlation with export volume change. The Pearson correlation coefficients are provided in the titles, indicating the strength and direction of these relationships.

The left plot shows that there was a negative correlation (Pearson = -0.26) between electricity imports and the change in the last month's sentiment: electricity imports seem to go up when the trend in sentiment gets more negative. Previous results confirmed this idea of dependency, which connects the duration of negative feelings with greater energy dependencyб possibly because crisis-driven demand leads to external electricity supply needs. The trend in the regression line is declining. Thus, more negative sentiments of last month seem to correlate with the following month's rise in electricity imports. However, the data points are dispersed to some degree. So, there may be some variance, which means that while the emotion does matter, other determinants may be involved in the import trends.

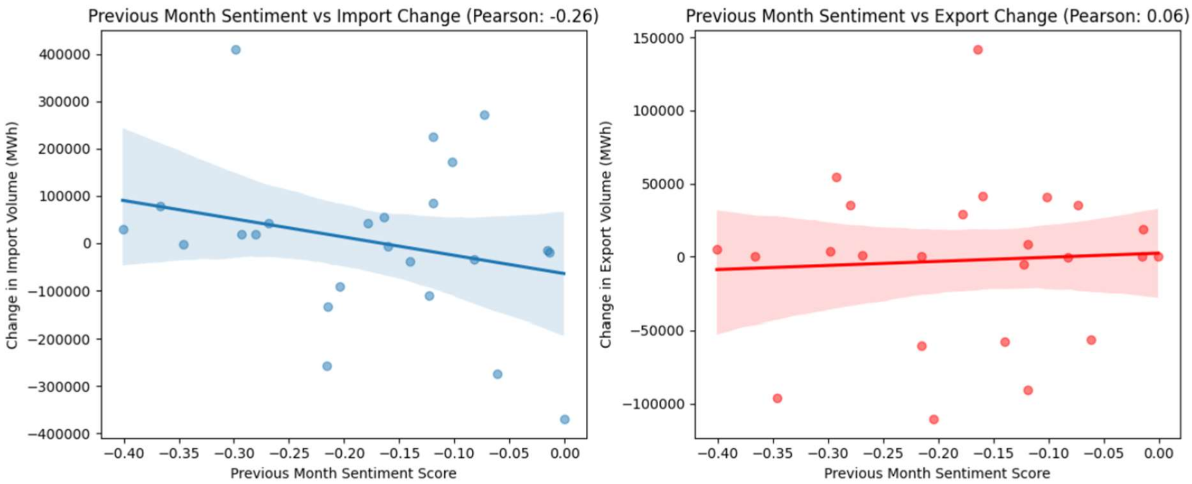


Figure 10: The scatter plot with correlation between the previous month's sentiment score and changes in electricity import and export volumes

The export change regression (right plot) shows a very weak positive correlation (Pearson = 0.06), suggesting that sentiment changes have little to no significant impact on electricity exports. The nearly flat regression line indicates that export volumes remain relatively stable regardless of sentiment fluctuations, reinforcing the observation that electricity exports may be governed by long-term agreements and market conditions rather than short-term sentiment trends.

There is a considerable correlation, with a negative sense associated with import changes that affirms the idea that negative sentiment score signal a higher reliance on electricity imports due to either impending or existing disturbances in domestic energy output. On the other hand, a very weak correlation with exports could indicate that exports react hardly at all to sentiment-driven fluctuations in the market, therefore stating that the import dependency would be more responsive to the news sentiment than stability in exports.

6. Discussions

This study revealed a very important link between news sentiment and electric trade mechanisms in Ukraine throughout the full-scale war. The analysis included the trends of sentiment, electricity import/export, and correlation among the statistics, all of which indicated that news sentiment represents a good indicator for market movement, especially under conditions of geopolitical instability.

The line chart analysis highlighted that prolonged periods of slightly negative sentiment changes were associated with a gradual increase in electricity imports, suggesting that sustained uncertainty leads to higher energy dependency. Moreover, sharp negative sentiment drops, such as in June 2024, correlated with immediate spikes in electricity imports, indicating that sudden deteriorations in sentiment may trigger crisis-driven import surges. This finding aligns with previous research on financial sentiment analysis, which suggests that negative media coverage can amplify economic uncertainty, leading to rapid market adjustments. The results also reinforce findings from "Opinion Mining of Green Energy Sentiment", where a spike in negative sentiment following the outbreak of the Russia-Ukraine war influenced public perception of energy security and policy acceptability. In both cases, sentiment acted as a leading indicator of market responses to crisis events.

Energy news in specific topics contributes in various ways to emotional changes by way of the topic modeling and sentiment analysis conducted per topic. The strongest absolute score for sentiment in relation to the most intense sentiment topic ("Topic 1") comes from the set: "war", "forces", "attack". Such information relates to emotions around missile strikes and destruction of energy infrastructure, being most emotional. On the other hand, "Topic 4", which was rich with the keyword's "power", "electricity", and "supply", has more balanced sentiment, with concern for shortage, yet it also discusses stabilization of supply. These findings confirm conclusion about mixed sentiment in social media discussions on energy policy and supply stability in the "EU Citizens' Discussions of the 2022–23 Energy Crisis". Furthermore, the fact that "Topic 3" included non-energy-related political discussion suggests that, on its own, using keywords to filter energy-related content is insufficient, and contextual-aware topic modeling methods should be utilized for improving accuracy in classifying news.

Analysis using linear regression showed a weak correlation (Pearson = -0.26) between sentiment and import volume change, thus proving that poor sentiment is a possible indicator for greater electricity imports in the following month [12]. The results from "Sentiment Analysis of Investors and Consumers in the Energy Market Using BERT-BiLSTM" (Cai et al., 2020) support the idea that negative sentiment has been shown to be linked to an increased risk-averse behavior in financial markets leading to shifts in investment and resource allocation. The correlation, however, between electricity exports and sentiment was weak (Pearson = 0.06), meaning the export volumes were hardly affected by the sentiment changes for a few days. Therefore, the short-term changes in sentiment had a negligible impact on exports; hence, it appears that long-term contracts, regulatory frameworks, and supply agreements are more decisive in export decisions, while imports are more reactive to the uncertainties in the market and crisis-driven sentiment changes.

However, these findings come with certain limitations. The GPT-4, being a context-aware classification model, is expensive in computation and non-scalable to large-scale big data [12]. In this case, GPT-4 was applied to a small dataset only. It is a right fit for pilot studies, however, future work should pursue a more efficient NLP model or a hybrid method when dealing with larger datasets [12]. Next, we should also bear in mind that shifts in sentiments do not influence electricity trade instantaneously, thus leading to the introduction of a one-month lag into the regression analysis. While this adjustment improved the correspondence between sentiments and trade patterns, there is further a need to work on the lag period and bring into the modeling additional economic and policy variables to strengthen them.

7. Conclusions

This study, in general, proves the applicability of sentiment analysis in better understanding energy trade dynamics during times of geopolitical crisis. The findings of this study show that the media sentiments are capable of being utilized as early warning signals for electricity import variations during periods of serious disruptions. Future studies could consider developing real-time monitoring techniques of sentiments, together with multi-modal information sources such as social media sentiment, expert opinions, and market indicators, which would serve to boost the accuracy of predictions made through sentiment-driven energy trade forecasting models [12].

The implemented approach on sentiment analysis and visualization seems quite effective under geopolitical disturbances is exemplified in a way to the war in Ukraine. It has been revealed that analyzed news is an important factor in understanding market responses during crises and, consequently, in the way uncertainties and disruptions affect electricity trading. However, it must be noted that there are some limitations: GPT-4 can classify sentiments adequately, although computational cost is so high that it becomes practically unfeasible for large analyses. Besides, regression analyses were carried out in a one-month gap, reinforcing correlation, this must also be tuned.

Declaration on Generative AI

During the preparation of this work, the authors used X-GPT-4 in order to: Grammar and spelling check.

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