IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 24 February 2023, accepted 10 March 2023, date of publication 15 March 2023, date of current version 21 March 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3257283

RESEARCH ARTICLE

Soaring Energy Prices: Understanding Public Engagement on Twitter Using Sentiment Analysis and Topic Modeling With Transformers

ZENUN KASTRATI[1], **ALI SHARIQ IMRAN**[2], **(Member, IEEE)**, **SHER MUHAMMAD DAUDPOTA**[3], **MUHAMMAD ATIF MEMON**[3], **AND MUHAMET KASTRATI**[4]

[1]Department of Informatics, Linnaeus University, 351 95 Växjö, Sweden
[2]Department of Computer Science, Norwegian University of Science and Technology (NTNU), 2815 Gjøvik, Norway
[3]Department of Computer Science, Sukkur IBA University, Sukkur 65200, Pakistan
[4]Department of Computer Science, University of New York Tirana, 1001 Tirana, Albania

Corresponding author: Zenun Kastrati (zenun.kastrati@lnu.se)

ABSTRACT Energy prices have gone up gradually since last year, but a drastic hike has been observed recently in the past couple of months, affecting people's thrift. This, coupled with the load shedding and energy shortages in some parts of the world, led many to show anger and bitterness on the streets and on social media. Despite subsidies offered by many Governments to their citizens to compensate for high energy bills, the energy price hike is a trending topic on Twitter. However, not much attention is paid to opinion mining on social media posts on this topic. Therefore, in this study, we propose a solution that takes advantage of both a transformer-based sentiment analysis method and topic modeling to explore public engagement on Twitter regarding energy prices rising. The former method is employed to annotate the valence of the collected tweets as positive, neutral and negative, whereas the latter is used to discover hidden topics/themes related to energy prices for which people have expressed positive or negative sentiments. The proposed solution is tested on a dataset composed of 366,031 tweets collected from 01 January 2021 to 18 June 2022. The findings show that people have discussed a variety of topics which directly or indirectly affect energy prices. Moreover, the findings reveal that the public sentiment towards these topics has changed over time, in particular, in 2022 when negative sentiment was dominant.

INDEX TERMS Sentiment analysis, energy price hike, topic modeling, transformers, BERT, Twitter, LDA, BERTopic.

I. INTRODUCTION

Energy is at the core of modern life - 21^{st} century humans heavily rely on energy to carry out basic life essential tasks including medical assistance, lighting, heating, cooling, transportation, home appliances, and much more. Due to the enormous reliance of humans on energy, it has also become an emotional issue. Any policy or price change related to energy by the government or corporate bodies, results in huge outrage from the public. In present times, probably the most convenient way of expressing such hue and cry is on social media where one can express all negative or positive views about any topic including energy. Indeed, the world has witnessed the change in governments due to the mismanagement of energy affairs and corresponding opinion expression on social media.

Twitter with 336 million active users monthly and around 500 million tweets per day become the main source of feedback for government, private organizations, and other service providers [1]. Obviously, processing such a huge number of tweets manually is impossible, therefore a sub-field of natural language processing, namely Sentiment Analysis (SA) has emerged as a solution to computationally process text for extracting people's opinions about the topic of interest.

The associate editor coordinating the review of this manuscript and approving it for publication was Hui Ma.

Sentiment Analysis is a research field that extracts users' opinions from target text and points out its related polarity (positive, negative or neutral). In recent years, SA has become a strong tool for tracking and understating users' opinions. In 2020, with the start of the pandemic, social media platforms, particularly Twitter played an essential role as communication channels to share people's reactions to coronavirus (covid-19) lockdown [2], [3], healthcare services [4], vaccination [5], [6], etc.

From January 2022 as the price of energy is dramatically increased, Twitter became a platform for people to react to such a rise. The spike in energy prices affected living costs for people all around the world. Due to rising energy prices, two-thirds (66%) of adults in Britain reported their cost of living increased during April 2022.[1] Moreover, according to Eurostat,[2] the Eurozone annual inflation rate is risen to 8.6% in June 2022, the highest since the creation of the Euro, mainly due to the soaring energy prices.

In the last two years with the huge oscillation in energy prices, makes it crucial to study and analyze public engagement on social media platforms. In this paper, we aim to investigate people's reactions to increases in energy bills that were expressed on Twitter from January 01, 2021 to June 18, 2022, and how the sentiment is developed over time. Additionally, the study aims to present experimental evaluation of various classifiers on sentiment analysis task. To that end, the collected tweets are initially annotated with sentiment labels using a transformer-based sentiment analysis approach and then a topic modeling based on BERTopic and LDA model is employed to identify other relevant hidden topics associated with energy prices for which people have shown positive and negative attitudes.

The following are major contributions of this paper:

- Creation of a dataset composed of 366,031 tweets related to energy prices collected between 01 January 2021 and 18 June 2022.
- A solution leveraging sentiment analysis and topic modeling to explore public engagement with soaring energy prices on social media, i.e. Twitter.
- Using a machine learning model based on transformers and lexicon based-approaches for the prediction of sentiment labels as well as continuous and discrete topic modeling.
- Benchmarking evaluation of various conventional machine learning and deep learning models on the collected Twitter dataset.
- Analysis of people's sentiment over time regarding energy issues world-wide.

The rest of the article is structured as follows. Section II presents the recent works. A description of transformer-based approach used to predict sentiment labels is presented in Section III-A. In Section IV, we present the methodology used to conduct the study. Section III-C briefly elaborates on two topic models employed to discover subtopics/themes from the dataset which is provided in Section V. Results and analysis are provided in Section VI. Finally, in Section VII, the conclusion and future directions are presented.

[1] https://www.bbc.com/news/business-60943192

[2] https://ec.europa.eu/eurostat/

II. RELATED WORK

Although social media sentiment mining has been well investigated over different topics and events, energy-related topics have not received much attention. In the past couple of years, there is a handful of papers concerned with examining public reactions on social media about various aspects related to energy such as clean energy, energy supply & services, nuclear energy, among others. For instance, the authors in [7] used a lexicon-based sentiment analysis to analyze sentiments expressed on Twitter by the UK energy company consumers. They optimised the accuracy of the sentiment analysis results by combining functions from two sentiment lexicons. They used two lexicons where the first one extracted the sentiment and the second lexicon to classify the rest of the data. According to their experimental results, this method improved the accuracy compared to the common practice of using only one lexicon.

The research work conducted in [8] used geo-tagged Twitter data collected from Alaska between 2014 and 2016 to investigate Alaskans' perceptions and opinions on clean energy sources. A lexicon-based sentiment analysis and fuzzy-based theory were employed to analyse the sentiment of each tweet. Their result shows the words "tidal" and "solar panel" have the highest rank among 20 other words. They also found that Alaskans' attitudes toward energy and renewable energy changed positively during the period of study. A similar study focusing on examining people's attitudes towards clean energy is conducted in [9]. In this study, the authors used Twitter data to do a comparative sentiment analysis on various renewable energy sources. Their results also confirmed that people are more positive towards renewable energy sources for a better environment. Similar results have been reported in [10], which shows that there exists a positive perception among people from the UK and Spain regarding renewable energy sources and a negative sentiment towards coal energy.

Some research efforts [11], [12], [13], [14] have been put into the investigation of public opinion on social media regarding nuclear energy. For instance, researchers in [12] analyzed Twitter discussions regarding nuclear disaster and energy. For this purpose, they collected a dataset of 2 million tweets concerning the Fukushima Nuclear Disaster in 2011 and the Nobel Peace Prize announcement in 2017. Three various deep neural networks including CNN, LSTM, and Bi-LSTM were used to analyze the attitude of users if they were supportive or cynical towards nuclear energy. The findings showed that the dominant aspects discussed by supportive users are more about concepts such as clean energy, lower CO2 emission, and a sustainable future, whereas cynical users viewed nuclear energy as unsafe for human life and threatening to the environment. Public opinion expressed on social media about nuclear energy is also investigated by the researchers in [15]. Specifically, the study focuses on examining the sentiment of people from German-speaking countries toward nuclear energy. Three machine learning algorithms, namely decision tree, random forest and LSTM are used for sentiment analysis. The study found that majority of the comments (71%) were neutral, followed by positive and negative comments that accounted for 23% and 6%, respectively. Opposite results have been reported in the research work conducted in [13] where the authors found that negative comments expressed by Korean people toward nuclear energy were larger than positive ones. Additionally, the study found that positive-tone articles were more present than negative ones.

A model for extracting people's opinions on several energy-related aspects is presented in [16]. The authors leveraged Twitter data using several word-embedding and deep neural models. More concretely, word embeddings are used for converting tweets to numerical representation, whereas BERT is employed for extracting people's sentiment from tweets. This approach is conceptually similar to ours but its focus and the approach used for the sentiment classification task are different. Specifically, we are focusing on exploring public engagement with energy prices on social media using transformer-based sentiment approaches as well as topic modeling for extracting various sub-themes.

There is another strand of research [17], [18], [19], [20] which focuses on exploring people's sentiment about renewable energy. For instance, researchers in [17] applied social media analytics to determine the emotional discourse on social media towards renewable energy. Analysis of 6528 Twitter messages about 27 electricity utilities in the US showed that sentiment varied based on utility with joy and sadness being the dominant emotions. Sentiment analysis of Twitter messages related to renewable energy companies is also examined in [20]. The study used a lexicon-based technique to extract investor sentiment from tweets during both trading and non-trading hours whereas stock forecast is carried out using a hybrid deep learning model (CNN-LSTM). The study found that sentiment variables play an import role on forecasting the stocks as they hold important information that can not be captured by standard financial market variables. Zhang et al. [21] proposed a study to assess user perception of renewable energy and GHG (greenhouse gas) emissions by analyzing Twitter mentions and Google search trends in the USA, Australia, and Europe.

Public sentiment expressed on Twitter regarding energy crisis has attracted the attention of researchers. For example, Vasiliki Vrana et al. [22] recently conducted a study to determine the sentiment of EU citizens on Twitter regarding energy crises. Using a multilingual sentiment analysis approach that considers five major European languages and English, the authors found that fear and sadness are the predominant emotions expressed by citizens in relation to energy crises. In another study, Zeitun et al. [23] analyzed sentiment expressed on Twitter and its impact on sectoral returns in the US. They found that opinion swings on Twitter not only affect the energy sector, but also impact other sectors such as healthcare, information technology, materials, and communication.

A summary of the reviewed studies including dimensions such as the domain of applications, year of publication, datasets, and models used to conduct the studies, is shown in Table 1.

Several of the studies that are mentioned above use social media data, primarily tweets, to determine how users feel about various energy related aspects. However, the study presented in this paper goes a step beyond that. In addition to conducting sentiment analysis related to energy prices, the proposed study also utilizes topic modeling to provide a more detailed explanation of the various aspects of user sentiment related to electricity prices. Moreover, our study employs a variety of sentiment classifiers including traditional machine learning techniques and deep learning models to predict the opinion of Twitters' users regarding energy prices.

III. BACKGROUND

In this section, we briefly outline the pseudo-labeling approaches utilized for tweets annotation including transformer-based as well as lexicon-based approaches.

A. TRANSFORMER-BASED APPROACH–BERT

Google's Bidirectional Encoder Representations from Transformers (BERT) is a transformer-based machine learning approach for natural language processing (NLP) pre-training. The original English-language BERT is available in two sizes: (1) the $BERT_{BASE}$, which has 12 encoders. 12 bidirectional self-attention heads and 768 hidden layers, and (2) the $BERT_{LARGE}$, which has 24 encoders, 16 bidirectional self-attention heads and 1024 hidden layers. Both models are pre-trained using unlabeled data gathered from BooksCorpus (800M words) and English Wikipedia (2,500M words).

Transformer is an attention mechanism that learns the contextual relationships between words (or subwords) in a text and is used by BERT. Transformer's basic design consists of two independent mechanisms: an encoder that reads the text input and a decoder that generates a prediction. Only the encoder mechanism is required because BERT's aim is to produce a language model. The following phrase in a sequence is frequently predicted by models (e.g. "The energy price is ___"), a directive approach that naturally restricts context learning. BERT employs two training techniques to overcome this obstacle including the Masked Language Model and Prediction of the Next Sequence, as illustrated in Figure 1.

1) MASKED LANGUAGE MODEL (MLM)

Word sequences are changed with a MASK token for 15% of the words in each sequence before being sent into the BERT. Based on the context offered by the other, non-masked, words in the sequence, the model then makes an effort to forecast the original value of the masked words. Technically speaking, the output words' prediction calls for:

TABLE 1. A tabular summary of the reviewed studies.

Ref.	Year	Domain	Dataset	Classification Models
[22]	2023	Energy	Twitter data	Lexicon-based approach for sentiment analysis
[23]	2023	Energy and other sectors	Twitter data	Twitter based investor sentiment index
[16]	2022	Energy-related issues	Twitter data	(Word2Vec, GloVe and FastText), (DNN, LSTM, Bi-LSTM, CNN)
[20]	2022	Renewable energy	Twitter	Lexicon-based Technique & CNN-LSTM
[15]	2022	Nuclear energy	Twitter data	Decision Tree, Random Forest and LSTM
[21]	2022	Renewable energy and GHG	Twitter & Google	Topic modelling through keyword similarity
[18]	2021	Renewable energy	Twitter data	Transformers (RoBERTa)
[13]	2021	Nuclear energy	NAVER portal	Lexicon-based approach
[12]	2020	Nuclear energy	Twitter data	CNN, LSTM, and Bi-LSTM
[10]	2020	Climate change & energy	Twitter data	Lexicon-based approach (EmoLex)
[8]	2020	Energy	Twitter data	A lexicon-based and a fuzzy methods
[19]	2019	Renewable Energy	Twitter data	SVM, KNN, Naïve Bayes, AdaBoost, Bagging
[14]	2019	Green buildings	Sina Weibo	Lexicon-based approach
[7]	2018	Energy	Twitter data	Two sentiment lexica
[11]	2018	Nuclear Energy	Twitter data	Attentive Deep Neural Network

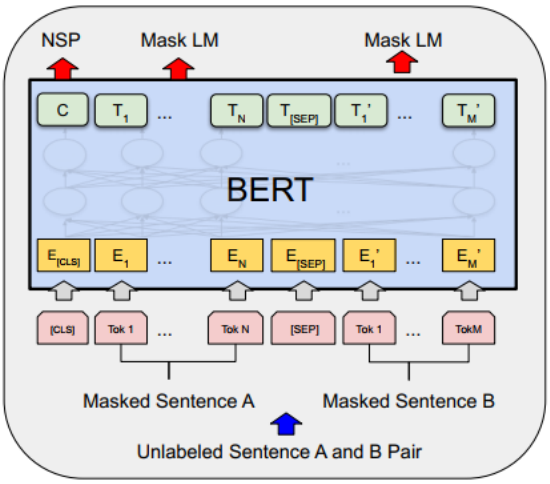


FIGURE 1. BERT using Masked Language Modeling [24].

- The output of the encoder is added to a classification layer.
- By dividing the output vectors by the embedding matrix, the vocabulary dimension is created.
- Use *softmax* to determine the likelihood of each word in the lexicon.

2) PREDICTION OF THE NEXT SENTENCE (NSP)

In the BERT training phase, the model learns to predict whether the second sentence in a pair will come after another in the original document by receiving pairs of sentences as input. During training, 50% of the inputs are pairs in which the second sentence is the next one in the original text, and in the remaining 50%, the second sentence is a randomly selected sentence from the corpus. The underlying presumption is that the second phrase will not be related to the first. The subsequent actions are taken in order to determine whether the second statement is, in fact, related to the first:

- The Transformer model processes the full input sequence.
- Using a straightforward classification layer, the [CLS] token's output is converted into a 21 shaped vector (learned matrices of weights and biases).
- Use *softmax* to determine the *IsNextSequence* probability.
- In order to reduce the combined loss function of the two techniques, MLM and NSP are learned jointly while training the BERT model.

Unquestionably, BERT represents a milestone in machine learning's application to natural language processing. Future practical applications are anticipated to be numerous given how easy it is to use and how quickly it can be fine-tuned.

B. LEXICON-BASED APPROACHES

A lexicon-based approach determines the sentiment of the whole text (tweet) by aggregating the semantic orientation (valence) of each word or phrase expressed in that text. The four most important and well-known lexicon-based approaches are briefly described in the following.

VADER that stands for Valence Aware Dictionary for Sentiment Reasoning is a text sentiment analysis that takes a human-centered approach, integrating qualitative analysis with empirical validation utilizing human raters and the wisdom of the public. It primarily uses a lexicon that converts lexical characteristics into sentiment scores, a representation of the intensity of an emotion. By adding the intensity of each word in a text, one may get the sentiment score of that text. The VADER sentiment analysis produces a sentiment score that ranges from -1 to 1, with 1 being the highest positive sentiment. The sentiment score of a sentence is determined by adding the sentiment ratings of all the words in the sentence that are included in the VADER lexicon.

TextBlob is a python library for Natural Language Processing that determines the sentiment of a tweet by calculating the semantic direction and the intensity of each word in that tweet. This necessitates the use of a pre-defined vocabulary that categorises negative and positive terms. TextBlob returns a sentence's polarity and subjectivity. Polarity is defined within the range of -1 and 1, where -1 represents a negative sentiment and 1 represents a positive sentiment. Subjectivity is a measure of the quantity of personal opinion and factual information in a writing and its values are between 0 and 1.

Flair is a framework for natural language processing built on PyTorch. It uses a pre-trained deep neural network to analyze the text and determine the sentiment expressed in that text. Contrary to VADER and TextBlob that generate a sentiment score in rage of -1 and 1, Flair produces a sentiment output with a confidence score between 0 and 1, with 1 indicating maximum confidence.

Stanza is a natural language processing framework that uses deep learning techniques to identify the sentiment expressed in a text. It uses annotator class named *SentimentProcessor* to add a sentiment label to each sentence in the text. Stanza supports negative, neutral and positive sentiment denoted by 0, 1, and 2, respectively.

C. TOPIC MODELING

Topic modeling is an unsupervised machine learning approach that represents each document as a mixture of a small number of topics or themes. Topics are represented by a set of highly co-occurring words in the document.

1) BERTopic

BERTopic [25] is a topic model that relies on word embeddings to generate topic representations. It involves three steps including document embeddings, dimension reduction and clustering, and topic representations. In the first step, each document (tweet) is converted to a dense vector through pre-trained language models. BERTopic provides various pretrained embedding models from *Sentence-BERT* framework. The second step in the model involves reducing the dimensionality of vector representations using the Uniform Manifold Approximation and Projection - UMAP algorithm. UMAP is a non-linear reduction technique that tries to learn the topological space (manifold) from data and then find out the lowest dimensional embedding that retains the crucial topological structure of that space. The reduced vectors are then grouped into clusters using HDBSCAN algorithm. HDBSCAN that stands for Hierarchical Density-Based Spatial Clustering of Application with Noise is a density based clustering algorithm that can handle datasets with noise and outliers. The idea behind this algorithm is to first find a "density" value for each data point using the closest points. Data points with high density values creates "core samples" that are then grouped together into clusters. In the last step, the model calculates the importance of words within a cluster through a modified *TF-IDF* representation called a class-based term frequency inverse document frequency (*c-TF-IDF*). *c-TF-IDF* for a word w in cluster c is computed using Equation 1.

$$W_{w,c} = tf_{w,c} * log(1 + \frac{\bar{X}}{tf_w}) \tag{1}$$

where, $tf_{w,c}$ indicates the frequency of word w in cluster c, tf_w shows frequency of word w across all clusters, and $\bar{X}$ denotes the average number of words per cluster.

2) LDA

Latent Dirichlet Allocation (LDA) is the simplest and most used [26] topic modeling technique. It uses a probabilistic model to discover topics from a text corpus. A topic is represented as a collection of co-occurring words whose importance is calculated using the Bag-of-Words algorithm. The main goal of LDA model is how to create a new document for each input document by maximizing the probability as defined in Equation 2.

$$\begin{aligned} p(w, z, \theta, \eta \mid \alpha, \beta) = \prod_{d=1}^{M} p(\theta_d \mid \alpha) \prod_{k=1}^{K} (p(\eta_k \mid \beta) \\ \prod_{t=1}^{N} p(z_{dt} \mid \theta_d) p(w_{dt} \mid \eta z_{dt}) \end{aligned} \tag{2}$$

where, α and β denote Dirichlet distributions, θ and η are multinomial distributions, z shows topics defined in all documents, w denotes all words in all documents, and M, K, N indicate the number of documents, number of topics and the number of words, respectively.

The output of the LDA model is two matrices including one defining probability distributions of topics and the other probability distribution of words relative to all topics.

IV. RESEARCH METHODOLOGY

To analyze people's engagement with energy price hike on Twitter, we employed a four-tier approach, as illustrated in Figure 2.

In the first layer referred to as Pseudo Labeling, we perform pseudo-labeling to predict sentiment labels for the collected unlabeled Twitter dataset. A machine learning model based on transformers and a lexicon-based approach are tested on a ground truth dataset to select the best performing labeling approach. Since there exist various lexicon-based approaches for sentiment analysis, we tested four of them, namely TextBlob, Vader, Flair, and Stanza. The ground truth composes of manually annotated tweets from SemEval-2013 [27] and SemEval-2015 [28] datasets created for the Twitter sentiment analysis task. We opted for the approach yielding the highest performance with respect to the ground truth to annotate the valence of the tweets (positive, negative or neutral), which initially undergo some pre-processing steps including removing duplicates, hashtags/mentions, URLs, emails, phone numbers, non-ASCII characters and converting all tweets to lowercase.

The second layer called Topic Modeling entails an unsupervised learning approach to find out what are the energy related aspects/topics for which people have talked positively and negatively. The dataset is divided into two sets - positive and negative tweets - which are fed into a topic modeling algorithm to learn the underlying topic structure. One topic modeling technique using transformer embeddings (BERTopic) and a generative Latent Dirichlet Allocation (LDA) model are applied to each positive and negative tweets set of the dataset. For the latter topic modeling approach,

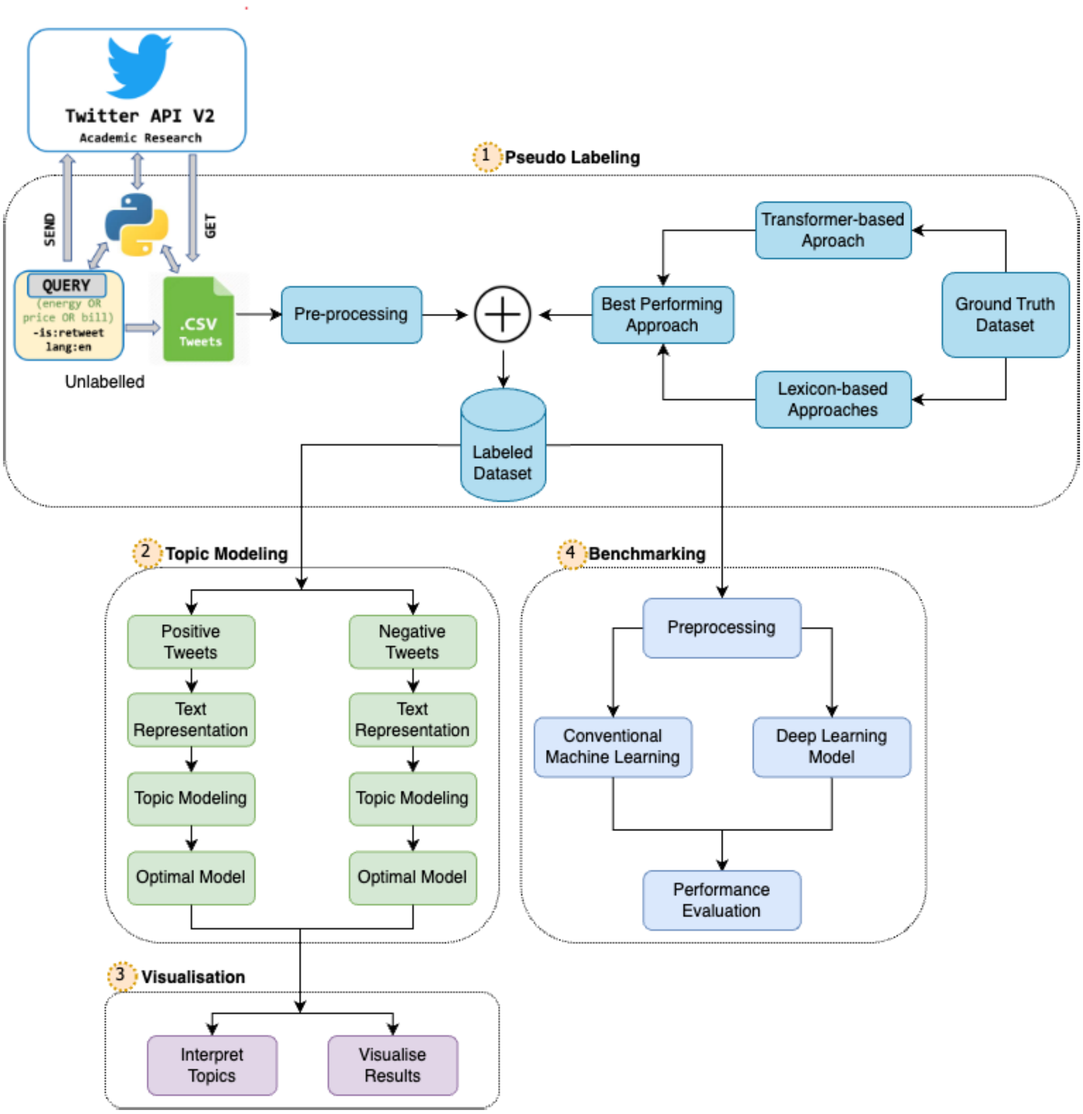


FIGURE 2. An abstract architecture of the proposed solution.

we generated various LDA models and an optimal model is selected using grid search and parameter tuning.

The third layer of the proposed solution, Visualisation, is involved in exploring, interpreting and visualisation of the results obtained from both the sentiment analysis and the topic modeling. It is primarily concerned with the representation of negative, neutral, and positive sentiments emerged from tweets, the development of the sentiment over time, and displaying and understanding of the topic model results accomplished by inspecting top 'n' words associated with the generated topics.

In the fourth layer captioned as Benchmarking, we benchmark a variety of conventional machine learning and deep learning models to determine which model is best suited for the prediction of people's sentiment toward energy prices. Specifically, we first perform pre-processing of labelled tweets where typical text processing steps such as removing punctuation and special characters, converting all characters to lowercase, and removing stop words and irrelevant words are applied. Next, the tweets dataset is split into two subsets, training and testing, and then fed into the classifier models to learn the underlying data patterns. Finally, the models' performance is evaluated and compared using information retrieval-based evaluation metrics like accuracy, precision, recall and F1-score.

V. DATASET

This section elaborates the dataset collection procedure and data labeling as well as presents dataset statistics.

A. DATASET COLLECTION

We collected a dataset comprising tweets to detect people's sentiment polarity towards energy prices. Users' tweets are fetched using a standard Twitter search API v2 for academic

TABLE 2. List of keywords and hashtags used to fetch tweets.

Keyword	Hashtag
Electricity price	#electricity_price
	#electricityPrice
Electricity bill	#electricity_bill
	#electricityBill
Electricity price hike	#electricity_price_hike
	#electricityPriceHike
Energy price	#energy_price
	#energyPrice
Energy bill	#energy_bill
	#energyBill

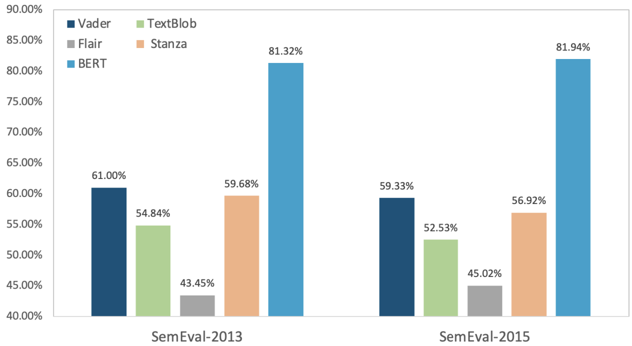


FIGURE 3. Accuracy of the predicted labeling approaches output with respect to the ground truth.

research product track using Python 3. The list of keywords and hashtags used to run the search on Twitter is shown in Table 2.

Tweets in English for the period January 1, 2021 to June 18, 2022 are cataloged for further processing including attributes like Tweet ID, text, user name, time, and location. As a result of this process, 452,505 tweets are fetched from Twitter. After pre-processing steps such as removing duplicates, non-English tweets, and null values that resulted in some cases after performing tweets cleansing, the number of tweets dropped to 366,031.

B. SELECTING THE SENTIMENT LABELING APPROACH

To select the model for sentiment labeling of collected tweets, we tested and compared the performance of four lexicon-based approaches and the BERT for sentiment analysis on a ground truth consisting of two benchmark datasets, known as SemEval-2013 and SemEval-2015. The former dataset contains 14,885 manually annotated tweets (positive: 5690, neutral: 6838, negative: 2357), whereas the latter comprises 2,879 tweets manually tagged as positive (1208), neutral (1240) and negative (431). Sentiment labels generated from all the labeling approaches are compared with the labels in the ground truth datasets and accuracy is computed, as illustrated in Figure 3.

As can be seen from Figure 3, BERT outperforms all lexicon-based sentiment labeling algorithms, achieving an accuracy of 81.32% on SemEval-2013 and 81.94% on SemEval-2015, respectively. Due to its good performance, we opted to only use BERT to tag tweets in our collected dataset with sentiment labels.

TABLE 3. Distribution of tweets across sentiment classes.

Sentiment class	# of tweets	Percentage (%)
Negative	165,522	45.22
Neutral	176,780	48.30
Positive	23,729	6.48
Total	366,031	100.00

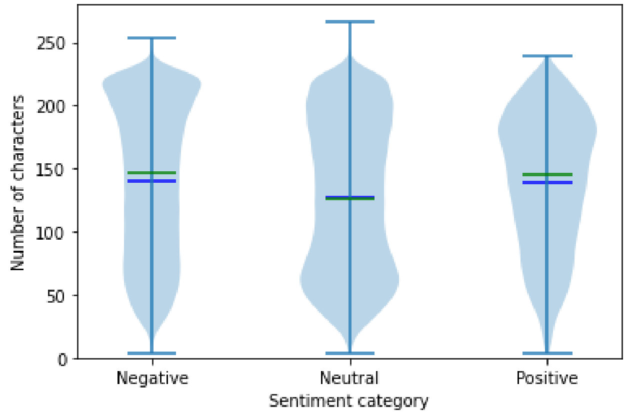


FIGURE 4. Length of tweets across sentiment categories.

C. DATASET LABELLING AND STATISTICS

The network architecture applied to predict sentiment labels is a fine-tuned BERT model [29] trained with SemEval-2017 corpus and based on a pre-trained language model for English tweets (BERTweet) trained on 850M English tweets.

The pseudo-labeling process results in tweets classified as either positive, neutral or negative. The distribution of tweets along sentiment classes is not uniform. Neutral tweets are dominant and account for 48.30% of the total samples of the dataset, followed by negative and positive tweets with 45.22% and 6.48%, respectively. The number and the percentage of tweets in each sentiment class are shown in Table 3.

The text content of tweets in our dataset is of different sizes, starting from 4 up to 266 characters, with an average of 133.7 characters per tweet. The variation of tweets length is shown in Figure 4, where box plots indicate the distribution of tweets along each sentiment category with respect to the number of characters.

As can be seen from Figure 4, neutral tweets are shorter compared to positive and negative ones. Specifically, neutral tweets containing less than 60 characters occur more frequently in this category. Contrarily, negative tweets are longer; tweets with more than 220 characters dominate the negative category of the dataset as indicated by the wider area of the violin box. Positive tweets are more scattered with an average length of 150 characters.

VI. EXPERIMENTAL RESULTS AND ANALYSIS

This section provides experiments conducted with topic modeling using BERTopic and LDA models to discover the sub-topics of discussion on the tweets dataset about energy prices.

A. TOPIC MODELING USING BERTopic

We trained our BERTopic model on the whole tweets dataset using default parameters for embedding model ($all - MiniLM - L6 - v2$), UMAP and HDBSCAN. For topic representation, a *CountVectorizer* model with 2-gram words and stopwords removed is used. The model outputs a list of topics sorted by frequency and we analyzed only the top 10 most frequent topics. To identify what the topics are, the top 10 words associated with each specific topic are revealed, as shown in Table 4.

As can be seen from the topic representations in Table 4, the first 5 identified topics are coherent and their interpretations are easy. Obviously, Topic 0 is about solar panels and solar energy. Topic 1 relates to Russia's invasion of Ukraine. The issue of Bitcoin mining and cryptocurrency is discussed in Topic 2. Topic 3 is about electric cars/vehicles, whereas Topic 4 seems to be about the electricity price hike. Topics 5, 6, 7, and 8, are more difficult to interpret as they contain mostly common words and capture a variety of themes into a single topic. The last topic (Topic 9) seems to pertain to nuclear and renewable energy in Germany.

Next, we analyzed the evolution of topics over time to understand how the Twitter discourse towards these topics has changed in the last two years. To achieve this, we initially extracted global topic representations from the dataset and then for each topic, we computed the topic representation at each timestamp using the dynamic topic modeling technique of BERTopic. The evolution of top 10 most frequent topics is visually illustrated in Figure 5.

As can be seen from the diagram in Figure 5, the first topic (Topic 0) concerning solar energy was the dominant topic over the entire 2021. The remaining 9 topics were represented almost equally, with an exception of the topic about bitcoin and crypto mining (Topic 2) that was more present in certain periods of the year. A similar trend can be seen for the year 2022, where people continued talking about these topics on Twitter. Exceptionally, it was the topic about the Russian invasion of Ukraine (Topic 1) which started to dominate by the end of January 2022, and continued to be a far more discussed topic during the rest of the year. Also, during March 2022, people started to comment more on the topic concerning electric vehicles (Topic 3).

Next, to validate our judgment about topics discovered using the most important words, we carried out a detailed observation of each topic by extracting the tweets that are assigned to them. For the sake of simplicity, we chose to present and discuss only one topic. The topic labeled as 'Solar energy' has tweets which talk about investing and installing solar panels as a measure to reduce high energy bills.

Figure 6 illustrating the three tweets in which the topic 'Solar energy' is the most important demonstrates high consistency between the topic model and tweets assigned to it.

Furthermore, to get better insights into public engagement with soaring energy price, we trained the BERTopic model on both positive and negative tweets to extract new themes or subtopics in the dataset for which people have expressed positive and negative opinion or attitude. The top 5 most frequent topics extracted from positive and negative tweets are illustrated in Figure 7.

As can be seen from Figure 7, meaningful topics are discovered from both sets of tweets, especially positive ones. Broader topics closely related to energy prices such as saving energy (T0), reducing taxes and VAT (T4), were discussed positively by people on Twitter along with specific topics that may have effects on lowering energy bills such as smart thermostats (T1) and tree planting (T2). On the other side, people have shown negative sentiment towards topics that greatly affected energy prices such as war in Ukraine (T0), the Biden administration's energy policy (T3), the high price of gas, oil and fuel (T4).

Lastly, we generated a word cloud for the entire corpus to investigate the most frequent words in the positive and negative tweets corpora. Stop words are removed from tweets. The results shown in Figure 8 generally confirm the result obtained from the topic modeling because words such as *energy*, *electricity*, *price*, *bills*, *help*, *support*, and *energy*, *electricity*, *price*, *bills*, *inflation*, etc., are seen to appear very often in positive and negative tweets, respectively.

To be able to draw conclusions about what each topic means, we extracted the top 10 most important words for each topic. For the sake of space, we present in Table 5 only the two most frequent topics, one from positive and one from negative tweets, and the top-10 words assigned to them (The full list of topics and their associated words is shown in Table 9 in Appendix A).

From the topic words given in Table 5, the first topic seems to be about planting trees as a strategy to save energy and to reduce high energy bills as it contains words such as *trees*, *planting*, *planting trees*, *energy*, *energy bills*, *reduce*. Whereas, the second topic seems to relate to the Russia-Ukraine war and its effect on the energy price, as it comprises words like *ukraine*, *energy*, *war*, *russia*, *electricity*, *bills*.

B. TOPIC MODELING USING LDA

Tweets are converted into an appropriate vector format that is supported by LDA models using term frequency inverse document frequency ($tf * idf$). The $tf * idf$ model is created for terms with three or more characters that occurred in more than 10 tweets and less than 90% of the tweets. This is done to keep only terms that convey a stronger signal about the semantic content of tweets and do not introduce noise to the model.

Next, we used a grid search strategy to find the best performing LDA model on our dataset. The grid search comprises the two most important tuning parameters including the number of topics (*n_topics*) with values in [5, 10, 15, 20, 25] and the learning rate (*learning_decay*) of the model with values ranging in [0.5, 0.7, 0.9]. The best model performance evaluated with perplexity and log-likelihood metrics is achieved by the LDA model with 5 topics and a learning rate of 0.7 on positive tweets and 0.5 on negative tweets set,

TABLE 4. Top 10 words associated with top 10 most frequent topics.

No	Topic 0	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9
1	solar	ukraine	bitcoin	ev	electricity	australia	prices	bill	lol	germany
2	panels	russia	mining	evs	price	auspol	marcorubio	electricity	wait	german
3	solarenergy	putin	miners	cars	prices	australian	energy	rip	yeah	germans
4	solarpanels	russian	crypto	tesla	increase	australians	price	bro	bills	germanys
5	solarpower	sactions	btc	car	hike	morrison	breaking911	imagine	jontricket	highest
6	rooftop	war	mine	charging	too	australias	jackposobiec	lol	my	energywende
7	pv	russias	miner	electric	thehill	nsw	wait	ur	love	nuclear
8	battery	invasion	cryptocurrency	vehicle	worry	south	go	pay	gonna	merkel
9	install	putins	profitable	vehicles	going	lnp	high	gonna	bill	europe
10	gosolar	ukrainian	pow	charge	go	labour	going	tho	energy	renewables

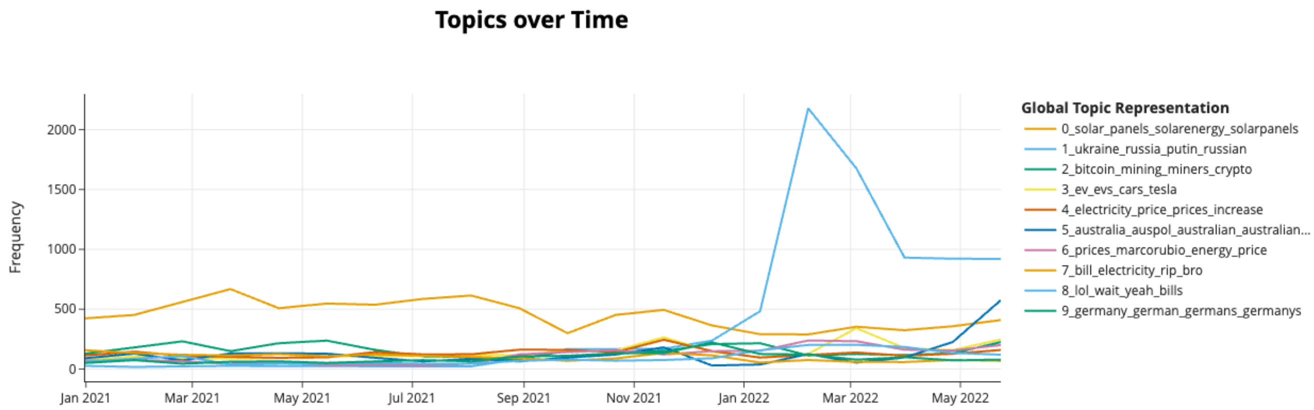


FIGURE 5. Evolution of top 10 most frequent topics over time.

Tweet 1:*"Go solar to bring down your energy bill the savings are amazing"*

Tweet 2: *"When solar panels were added to our house, they weren't allowed to cover the whole roof because that would capture too much energy and zero out our electricity bill"*

Tweet 3: *"Sorry, just solar panels to cut the electricity bills for large uniplexes"*

FIGURE 6. Tweets assigned to the topic 'Solar energy'.

TABLE 5. Topics and their associated words.

Topic	Top-10 words
Tree planting for lower energy bills	trees, tree, planting, shade, energy, plant, planting trees, tree today, energy bills, reduce
Ukraine war and energy crisis	ukraine, energy, nuclear, russia, putin, electricity, war, europe, russian, bills

respectively. Two topics extracted from positive and negative tweets and their topical words are shown in Table 6. (The list of topics and their associated words is shown in Table 10 in Appendix A).

Observing topics and their extracted words reveals that the BERTopic gives more coherent and interpretable topics compared to conventional LDA due to its capability to capture the semantic relationship among words using transformer embeddings [25].

TABLE 6. Topics and their associated words.

Topic	Top-10 words
Energy saving	energy, save, money, tips, bills, help, saving, home, electricity, ways
Inflation and high prices	prices, energy, inflation, price, high, rising, food, electricity, supply, higher

C. DEVELOPMENT OF THE SENTIMENT OVER TIME

We examined the evolution of the sentiments over time and tried to correlate positive and negative sentiment surges with the events that happened during those 18 months. Figure 9 illustrates the evolution of the sentiments over time, starting from January 01, 2021 until June 18, 2022. Tweets posted per each day are counted and normalized in the range of 0 and 1 by using *minmax* scaling method given in Equation 3.

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{3}$$

where, x' is the normalized number of tweets posted on a given day, x indicates the total number of tweets in that day, and *min* and *max* denote the lowest and highest number of tweets in the whole dataset, respectively.

As can be seen from the illustration in Figure 9, neutral tweets dominate the first three quarters of 2021, meaning

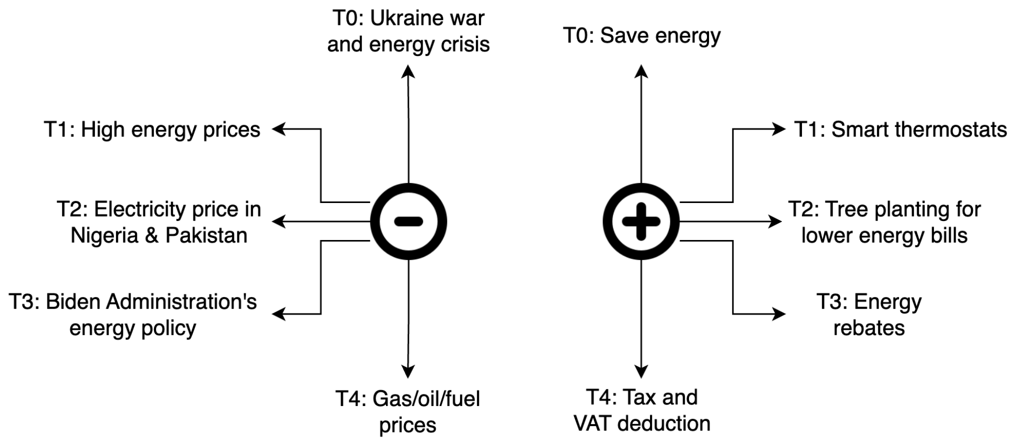
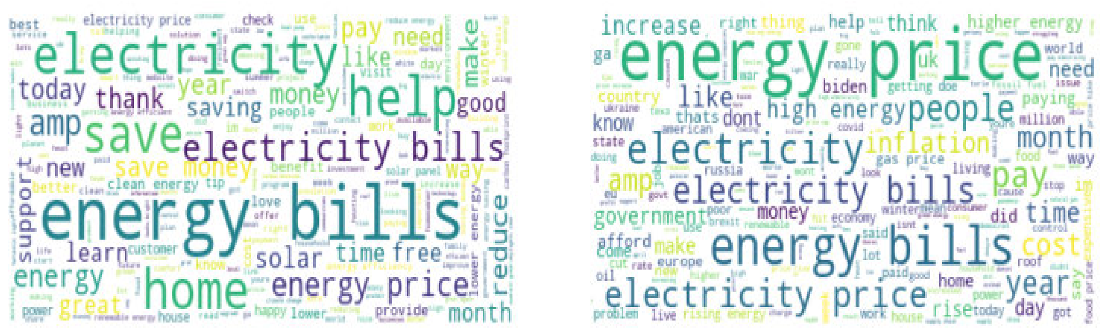


FIGURE 7. Top 5 most frequent topics extracted from negative (−) and positive (+) tweets using BERTopic.



(a) Positive tweets

(b) Negative tweets

FIGURE 8. Word cloud for positive and negative tweets.

TABLE 7. Deep learning architectures.

Model Name	Model Configuration/Parameters
DNN	Embedding Layer with 100 dimensions, GlobalMaxPooling1D, Layers with 128, 64, 32 with ReLU, Dense 3 with Softmax
1D-CNN	Embedding Layer with 300 dimensions, Layers with 64, 32 with ReLU, GlobalMaxPooling1D, Dense 32 with ReLU, Dense 3 with Softmax
BiLSTM + GloVe	Embedding Layer with 300 dimensions, BiLSTM Layers with 128, 64, 32 with ReLU, GlobalMaxPooling1D, Dense 10 with ReLU, Dense 3 with Softmax
BiLSTM + GloVe Twitter	Embedding Layer with 200 dimensions, BiLSTM Layers with 128, 64, 32 with ReLU, GlobalMaxPooling1D, Dense 10 with ReLU, Dense 3 with Softmax
BiLSTM + FastText	Embedding Layer with 300 dimensions, BiLSTM Layers with 128, 64, 32 with ReLU, GlobalMaxPooling1D, Dense 10 with ReLU, Dense 3 with Softmax
BERT	L=12 hidden layers (i.e., Transformer blocks), a hidden size of H=768, and A=12 attention heads, Dense 3 with Softmax

TABLE 8. Performance of conventional machine learning algorithms and deep learning models.

Model Name	Acc (%)	P (%)	R (%)	F1 (%)
NB	73.1	73.6	73.1	72.0
LR	77.3	77.3	77.3	77.0
SVM	76.6	76.6	76.6	76.3
RF	61.1	63.0	61.0	56.6
DT	55.1	57.1	55.1	53.1
BERT	67.1	65.8	67.1	66.8
DNN	78.4	78.8	78.4	78.5
1D-CNN	80.3	80.3	80.3	80.2
BiLSTM + GloVe	83.3	83.3	83.3	83.2
BiLSTM + GloVe Twitter	83.7	83.6	83.7	83.6
BiLSTM + FastText	84.1	84.2	84.1	84.2

that people were indifferent toward energy prices during this period. The situation started to gain more attention by the end of September 2021 when the negative sentiment started growing unexpectedly. This surge of negative opinions was mostly correlated with the approach of the UK prime minister to the energy crisis saying it was a ‘short-term issue’ and with the UK Government’s decisions on cutting the universal credit and supporting energy suppliers with state-backed loans. After this period, we see that the sentiment appears to be turning positive and continues till the last week of February 2022. The positive attitude of people expressed during this period can be associated with the ‘Communication on Energy Prices’ adopted by the European Commission, as a response to the rapid increase in global energy prices. The Communication covers a toolbox that helps to mitigate the impact of high energy prices for vulnerable people and small businesses across the European Union and its Member States during the winter. From the last week of February 2022,

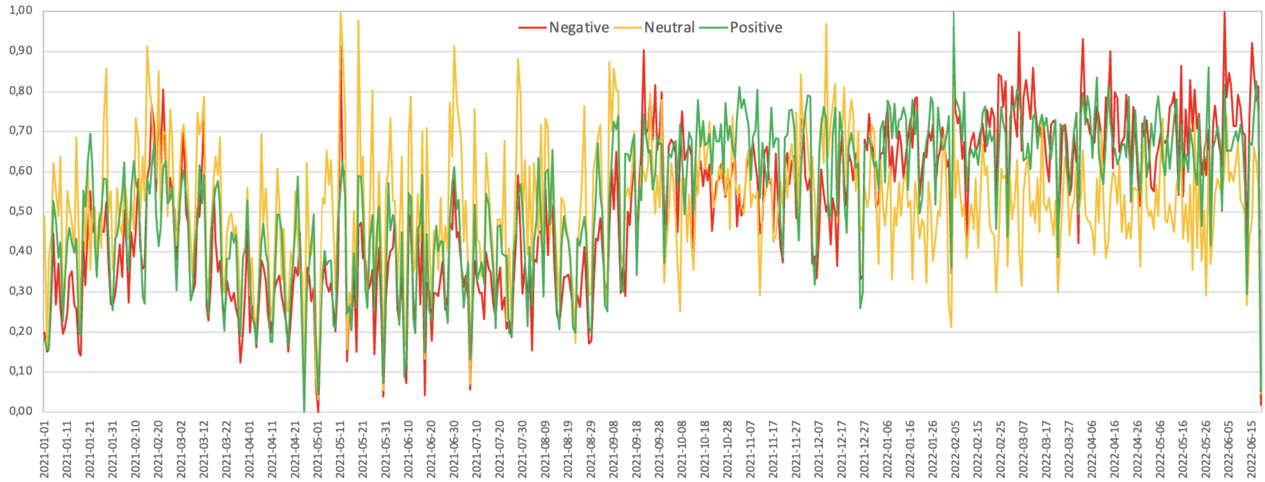


FIGURE 9. **Development of the sentiments over time.**

we can observe that the negative tweets towards energy prices dominate the dataset and this correlates with the start of the Ukraine war.

It is also interesting to observe both the most negative and positive sentiment in the considered period. The positive sentiment reached its peak on February 04, 2022 and this is connected with the support scheme of 350 million pounds announced by the UK Government one day before to help millions of households with global energy prices. Whereas, the most negative sentiment is shown on June 03, 2022, which corresponds with the date when the EU imposed a partial ban on Russian oil. People have commented on this topic claiming that the ban would directly effect energy prices.

D. BENCHMARKING RESULTS

We carried out a benchmark evaluation where we evaluate five conventional machine learning algorithms and six deep learning models for predicting the sentiment of tweets. Conventional machine learning consists of parametric and non-parametric models including Naive Bayes (NB), Logistic Regression (LR), Support Vector Machines (SVM), Random Forest (RF) and Decision Tree (DT). All parameter values of these models are set to default. Deep learning comprises various models and architectures as well as three different embedding schemes, as shown in Table 7.

As can be seen from the experimental results summarized in Table 8, deep learning models have performed significantly better than traditional machine learning models, except the BERT which has achieved a lower performance. One possible reason for this could be the nature of the dataset which is specific to the domain of energy price and the BERT could not be able to learn domain-specific features as effectively as other models, i.e. BiLSTM and CNN, that are specifically fine-tuned on this domain. It is interesting to note that BiLSTM with FastText embedding of 300 dimensions has outperformed all the models, achieving an F1-score of 84.2%. This performance is slightly better than combining BiLSTM with GloVe and GloVe Twitter embeddings, and an explanation for this is that FastText embeddings are trained on character n-grams as well as words, which allows them to capture word parts such as prefixes and suffixes.

VII. CONCLUSION AND FUTURE WORK

In this paper, we examined people's reactions toward energy price hike expressed on social media. An unsupervised solution leveraging Twitter data was applied. We initially employed BERT to divide tweets into neutral, positive and negative, and then a topic modeling based on BERTopic and LDA is used to identify relevant sub-topics associated to energy prices from both positive and negative tweets subsets. To find a suitable number of topics/themes in the LDA, we tested various models using a grid search approach and the best performing model with five topics was selected.

Findings showed that people discussed various topics that have direct effects on energy prices and this could help the decision-makers such as Government agencies and energy actors, to understand the public sentiment towards these topics and take the appropriate actions to deal with them. The decision-makers also should increase the public awareness on many of the identified topics like tree planting, solar energy, crypto mining, electric vehicles, as a measure to save energy and help consumers reduce energy bills.

We also investigated people's reactions toward identified topics and how the sentiment has changed over time. At the beginning of the considered period, people seemed to pay not much attention to the situation, but the last quarter of 2021 and half of the first quarter of 2022 were characterized by positive sentiments due to various supporting schemes introduced by different governments to help people pay high energy bills. The last period, starting from the end of February 2022, was dominated by negative sentiments due to the unexpectedly raising prices of energy/oil/gas because of the Ukraine war.

In this study, we leveraged Twitter data posted only this year and the previous one, therefore, future work will be

TABLE 9. Top 10 words extracted using BERTopic.

Positive tweets				
Topic 0	Topic 1	Topic 2	Topic 3	Topic 4
energy	thermostat	trees	rebate	vat
bills	smart	tree	council tax	vat energy
electricity	smart thermostat	planting	tax	cut
energy bills	save	shade	council	energy bills
save	thermostats	energy	rebates	cutting vat
amp	energy	plant	150	bills
help	nest	planting trees	eligible	vat cut
home	smart thermostats	tree today	energy rebate	cutting
money	energy bills	energy bills	jci	cut vat
great	help	reduce	150 council	energy
Negative tweets				
Topic 0	Topic 1	Topic 2	Topic 3	Topic 4
ukraine	electricity prices	pakistan	biden	amp
energy	month	australia	bidens	electricity
nuclear	electricity price	nigeria	joe biden	energy
russia	prices	nigerians	joe	gas
putin	electricity	australians	biden administration	fuel
electricity	energy prices	imran	administration	prices
war	prices going	khan	prices biden	price
europé	prices electricity	australian	president	oil
russian	high	south	policies	bills
bills	going	australias	energy	electricity price

TABLE 10. Top 10 words extracted using LDA.

Positive tweets				
Topic 0	Topic 1	Topic 2	Topic 3	Topic 4
energy	solar	energy	energy	electricity
save	energy	prices	bills	pay
money	bills	clean	help	love
tips	electricity	bills	home	bills
bills	save	amp	local	thank
help	home	climate	support	help
saving	reduce	jobs	save	energy
home	help	lower	amp	just
electricity	power	air	electricity	pay
ways	great	electricity	people	paying
Negative tweets				
Topic 0	Topic 1	Topic 2	Topic 3	Topic 4
electricity	energy	prices	energy	prices
pay	bills	energy	bills	energy
bills	prices	inflation	prices	gas
month	people	price	people	biden
paying	electricity	high	electricity	high
dont	amp	rising	going	higher
just	texas	food	price	oil
energy	high	electricity	pay	electricity
like	inflation	supply	tax	green
high	food	higher	rise	amp

focusing on collecting more tweets going back in years. Also, the dataset used in this article is highly imbalanced (positive tweets are underrepresented), so as a future work we plan to use sampling-based and text generation techniques, i.e GAN-based models [30] and GPT [31] for balancing the dataset and assess its impact on overall classification performance.

APPENDIX. A

Table 9 and 10 show top 5 topics along with their top 10 topical words extracted from positive and negative tweets using BERTopic and LDA model, respectively.

REFERENCES

[1] R. Ahuja, A. Chug, S. Kohli, S. Gupta, and P. Ahuja, "The impact of features extraction on the sentiment analysis," *Proc. Comput. Sci.*, vol. 152, pp. 341–348, Jan. 2019.

[2] A. S. Imran, S. M. Daudpota, Z. Kastrati, and R. Batra, "Cross-cultural polarity and emotion detection using sentiment analysis and deep learning on COVID-19 related tweets," *IEEE Access*, vol. 8, pp. 181074–181090, 2020.

[3] Z. Kastrati, L. Ahmedi, A. Kurti, F. Kadriu, D. Murtezaj, and F. Gashi, "A deep learning sentiment analyser for social media comments in low-resource languages," *Electronics*, vol. 10, no. 10, p. 1133, May 2021.

[4] E. Ainley, C. Witwicki, A. Tallett, and C. Graham, "Using Twitter comments to understand people's experiences of UK health care during the COVID-19 pandemic: Thematic and sentiment analysis," *J. Med. Internet Res.*, vol. 23, no. 10, 2021, Art. no. e31101.

[5] R. Marcec and R. Likic, "Using Twitter for sentiment analysis towards AstraZeneca/Oxford, Pfizer/BioNTech and Moderna COVID-19 vaccines," *Postgraduate Med. J.*, vol. 98, no. 1161, pp. 544–550, Jul. 2022.

[6] R. Batra, A. S. Imran, Z. Kastrati, A. Ghafoor, S. M. Daudpota, and S. Shaikh, "Evaluating polarity trend amidst the coronavirus crisis in Peoples' attitudes toward the vaccination drive," *Sustainability*, vol. 13, no. 10, p. 5344, May 2021.

[7] V. Ikoro, M. Sharmina, K. Malik, and R. Batista-Navarro, "Analyzing sentiments expressed on Twitter by UK energy company consumers," in *Proc. 5th Int. Conf. Social Netw. Anal., Manage. Secur. (SNAMS)*, Oct. 2018, pp. 95–98.

[8] M. Abdar, M. E. Basiri, J. Yin, M. Habibnezhad, G. Chi, S. Nemati, and S. Asadi, "Energy choices in Alaska: Mining people's perception and attitudes from geotagged tweets," *Renew. Sustain. Energy Rev.*, vol. 124, May 2020, Art. no. 109781.

[9] A. Jain and V. Jain, "Renewable energy sources for clean environment: Opinion mining," *Asian J. Water, Environ. Pollut.*, vol. 16, no. 2, pp. 9–14, Apr. 2019.

[10] M. L. Loureiro and M. Alló, "Sensing climate change and energy issues: Sentiment and emotion analysis with social media in the U.K. and Spain," *Energy Policy*, vol. 143, Aug. 2020, Art. no. 111490.

[11] Z. Liu and J.-C. Na, "Aspect-based sentiment analysis of nuclear energy tweets with attentive deep neural network," in *Maturity and Innovation in Digital Libraries*, M. Dobreva, A. Hinze, and M. Žumer, Eds. Cham, Switzerland: Springer, 2018, pp. 99–111.

[12] A. Khatua, E. Cambria, S. S. Ho, and J. C. Na, "Deciphering public opinion of nuclear energy on Twitter," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2020, pp. 1–8.

[13] S. Y. Jeong, J. W. Kim, Y. S. Kim, H. Y. Joo, and J. H. Moon, "Sentiment analysis of nuclear energy-related articles and their comments on a portal site in Rep. of Korea in 2010–2019," *Nucl. Eng. Technol.*, vol. 53, no. 3, pp. 1013–1019, Mar. 2021.

[14] X. Liu and W. Hu, "Attention and sentiment of Chinese public toward green buildings based on Sina Weibo," *Sustain. Cities Soc.*, vol. 44, pp. 550–558, Jan. 2019.

[15] H. Xu, T. Tang, B. Zhang, and Y. Liu, "Automatic sentiment analysis of public opinion on nuclear energy," *Kerntechnik*, vol. 87, no. 2, pp. 167–175, Apr. 2022.
[16] J. Bedi and D. Toshniwal, "CitEnergy: A BERT based model to analyse citizens' energy-tweets," *Sustain. Cities Soc.*, vol. 80, May 2022, Art. no. 103706.
[17] J. Corbett and B. T. R. Savarimuthu, "From tweets to insights: A social media analysis of the emotion discourse of sustainable energy in the United States," *Energy Res. Social Sci.*, vol. 89, Jul. 2022, Art. no. 102515.
[18] S. Y. Kim, K. Ganesan, P. Dickens, and S. Panda, "Public sentiment toward solar energy—Opinion mining of Twitter using a transformer-based language model," *Sustainability*, vol. 13, no. 5, p. 2673, Mar. 2021.
[19] A. Jain and V. Jain, "Sentiment classification of Twitter data belonging to renewable energy using machine learning," *J. Inf. Optim. Sci.*, vol. 40, no. 2, pp. 521–533, Feb. 2019.
[20] G. P. Herrera, M. Constantino, J.-J. Su, and A. Naranpanawa, "Renewable energy stocks forecast using Twitter investor sentiment and deep learning," *Energy Econ.*, vol. 114, Oct. 2022, Art. no. 106285.
[21] Y. Zhang, M. Abbas, and W. Iqbal, "Perceptions of GHG emissions and renewable energy sources in Europe, Australia and the USA," *Environ. Sci. Pollut. Res.*, vol. 29, no. 4, pp. 5971–5987, Jan. 2022.
[22] V. Vrana, D. Kydros, I. Kotzaivazoglou, and I. Pechlivanaki, "EU citizens' Twitter discussions of the 2022–23 energy crisis: A content and sentiment analysis on the verge of a daunting winter," *Sustainability*, vol. 15, no. 2, p. 1322, Jan. 2023.
[23] R. Zeitun, M. U. Rehman, N. Ahmad, and X. V. Vo, "The impact of Twitter-based sentiment on U.S. sectoral returns," *North Amer. J. Econ. Finance*, vol. 64, Jan. 2023, Art. no. 101847.
[24] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," 2018, *arXiv:1810.04805*.
[25] M. Grootendorst, "BERTopic: Neural topic modeling with a class-based TF-IDF procedure," 2022, *arXiv:2203.05794*.
[26] C. B. Asmussen and C. Møller, "Smart literature review: A practical topic modelling approach to exploratory literature review," *J. Big Data*, vol. 6, no. 1, pp. 1–18, Dec. 2019.
[27] P. Nakov, S. Rosenthal, Z. Kozareva, V. Stoyanov, A. Ritter, and T. Wilson, "SemEval-2013 task 2: Sentiment analysis in Twitter," in *Proc. 2nd Joint Conf. Lexical Comput. Semantics (SEM)*, vol. 2. Atlanta, GA, USA, Jun. 2013, pp. 312–320.
[28] S. Rosenthal, P. Nakov, S. Kiritchenko, S. Mohammad, A. Ritter, and V. Stoyanov, "SemEval-2015 task 10: Sentiment analysis in Twitter," in *Proc. 9th Int. Workshop Semantic Eval. (SemEval)*, Jun. 2015, pp. 451–463.
[29] R. Lamsal, A. Harwood, and M. R. Read, "Twitter conversations predict the daily confirmed COVID-19 cases," *Appl. Soft Comput.*, vol. 129, Nov. 2022, Art. no. 109603.
[30] A. S. Imran, R. Yang, Z. Kastrati, S. M. Daudpota, and S. Shaikh, "The impact of synthetic text generation for sentiment analysis using GAN based models," *Egyptian Informat. J.*, vol. 23, no. 3, pp. 547–557, Sep. 2022.
[31] S. Shaikh, S. M. Daudpota, A. S. Imran, and Z. Kastrati, "Towards improved classification accuracy on highly imbalanced text dataset using deep neural language models," *Appl. Sci.*, vol. 11, no. 2, p. 869, Jan. 2021.

ZENUN KASTRATI received the master's degree in computer science through the EU TEMPUS Program developed and implemented jointly by the University of Pristina, Kosovo, Universite de La Rochelle, France, and the Institute of Technology Carlow, Ireland, and the Ph.D. degree in computer science from Norwegian University of Science and Technology (NTNU), Norway, in 2018. He is currently with the Department of Informatics, Linnaeus University, Sweden. He is the author of more than 50 peer-reviewed journals and conference papers. His research interests include artificial intelligence, with a special focus on NLP, machine/deep learning, and sentiment analysis. He has served as a reviewer for many reputed journals over the years.

ALI SHARIQ IMRAN (Member, IEEE) received the master's degree in software engineering and computing from the National University of Sciences and Technology (NUST), Pakistan, in 2008, and the Ph.D. degree in computer science from the University of Oslo (UiO), Norway, in 2013. He is currently an Associate Professor with the Department of Computer Science, Norwegian University of Science and Technology (NTNU), Norway. He is a member of the Norwegian Colour and Visual Computing Laboratory (Colourlab). He specializes in applied research with a focus on deep learning technology and its application to signal processing, natural language processing, and semantic web. He has over 65 peer-reviewed journals and conference publications to his name. He served as a reviewer for many reputed journals over the years, including IEEE Access, as an Associate Editor.

SHER MUHAMMAD DAUDPOTA received the master's and Ph.D. degrees from Asian Institute of Technology, Thailand, in 2008 and 2012, respectively. He is currently a Professor of computer science with Sukkur IBA University, Pakistan. Alongside his computer science contribution, he is also a quality assurance expert in higher education. He is the author of more than 35 peer-reviewed journals and conference publications. His research interests include deep learning, natural language processing, and video and signal processing. He has reviewed more than 50 universities in Pakistan for quality assurance on the behalf of the Higher Education Commission in the role of Educational Quality Reviewer.

MUHAMMAD ATIF MEMON received the bachelor's degree, in 2016, and the master's degree with the specialization in data knowledge and engineering from Sukkur IBA University, Mirpurkhas Campus, in 2020. He is currently with the Department of Computer Science, Sukkur IBA University. His research interests include artificial intelligence, machine learning, image mining, deep learning, and sentiment analysis.

MUHAMET KASTRATI received the B.Eng. and M.Sc. degrees in computer engineering from the University of Prishtina, Kosovo, in 2007 and 2014, respectively. He is currently pursuing the Ph.D. degree with the Department of Computer Science, University of New York Tirana, Albania. His research interests include machine learning and deep learning and its application to natural language processing, and social network analysis.