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Forecasting Hourly Electricity Prices in European Nations: Utilizing Machine Learning and Deep Learning Techniques for Sustainable Energy Decision-Making

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Abstract- Machine learning and deep learning techniques are used to anticipate hourly power costs for European countries (France, Italy, Belgium, Spain, the UK, and Germany). The research intends to develop exact forecast models based on past power pricing data through data visualization and model evaluation. Accurate forecasting is improved by studying seasonality patterns and price trends in various countries. In order to understand pricing changes, the study looks into international interdependence. It also offers useful information to energy sector players, facilitating better energy trading, grid stability, and environmentally friendly decision-making. The suggested methodology accurately forecasts electricity prices, encouraging the use of clean and effective energy sources.
Keywords- Decision Tree, Random Forest models, electricity, prices, energy, stability, LSTM

I. Introduction

A variety of machine learning and deep learning techniques are used to forecast electricity prices for different European nations. They examine trends, correlations, and distribution patterns using visualizations such as line plots, bar plots, correlation heat maps, histograms, and scatter plots to examine historical electricity price data for France, Italy, Belgium, Spain, the UK, and Germany. The researchers also use Decision Tree and Random Forest models to forecast electricity prices in the future using past data. By utilizing these techniques, energy sector stakeholders acquire insightful information that helps them to improve energy trade, grid stability, and overall energy efficiency, resulting in more sustainable and well-informed decision-making.

Aim and objectives.

Aim

The main aim of this is to optimize energy trade and improve energy efficiency and forecast hourly electricity prices for European nations (France, Italy, Belgium, Spain, UK, and Germany) using machine learning and deep learning techniques.

Objectives

- To create precise forecast models using past electricity price information.
- To use data visualization to examine seasonality and price trends.
- To analyze model performance using relevant comparison measures.
- To recognize international dependencies to comprehend price variations.
- To give stakeholders useful information so they may make wise decisions in the energy sector.

Research Question

- Using historical data, can machine learning and deep learning algorithms predict hourly electricity prices for European countries accurately?
- How are seasonality patterns and electricity price trends different in the selected European nations, and how can this knowledge be used to increase forecasting accuracy?
- How accurate and reliable are they in comparison to which machine learning and

deep learning models perform the best at forecasting hourly electricity prices?

- How these links affect changes in price do are there any notable relationships or dependencies between the pricing of energy in other nations?
- How can precise hourly electricity price projections assist market participants, utilities, and policymakers in enhancing grid stability, promoting sustainable energy practices, and optimizing energy trading strategies?

II. Background

This project is focused on the vital importance of projecting electricity prices in the energy industry. Accurate price forecasting has become crucial for market participants, utility companies, and policymakers due to the complexity of the energy markets and the increased emphasis on sustainable energy management. Stakeholders optimize energy trade, improve system stability, and advance effective resource allocation by using electricity price forecasts [1]. Several European nations, including France, Italy, Belgium, Spain, the UK, and Germany, are represented in the dataset under review as well as historical data on electricity prices. The information includes hourly electricity rates that are tallied over a predetermined time. The researchers want to investigate and create reliable predictive models that foresee changes in electricity prices for the aforementioned countries using this dataset. Various methodologies and procedures have been employed to anticipate the hourly electricity prices. These forecasts are created on an hourly basis, giving precise information about daily price changes. For hourly forecasts, a variety of algorithms have been used, including LSTM (Long Short-Term Memory) neural networks, Decision Trees, and other machine learning models. Each model contributed a set of distinct advantages to the forecasting process, capturing various dependencies and patterns in the data [2]. The forecasts are based on historical power price information, which included hourly prices in the past for numerous European nations. The models developed their ability to recognize patterns, seasonality, and other important characteristics that affected electricity pricing by making use of this historical data.

The researchers plan to use a variety of deep learning and machine learning techniques to accomplish this goal. It tries to identify underlying patterns, trends, and correlations in the data using visualizations like Line Plots, Bar Plots, Correlation Heat maps, Histograms, and Scatter Plots. These observations crucial building blocks for developing precise forecasting models [3]. The researchers want to use two machine learning models, Decision Tree and ***Random Forest*** to specifically estimate future power prices based on historical patterns. Utilizing the right measures, the forecasting accuracy was assessed by determining how well each model represented the real hourly price fluctuations [4]. This assessment made it possible to compare and choose the best prediction technique for each nation. Ultimately, utility companies, policymakers, and participants in the energy market all find great value in the hourly estimates of power prices. These projections provide essential information for controlling grid stability, optimizing energy trading tactics, and making knowledgeable decisions to increase overall energy efficiency. They seek to determine the best strategy for projecting power prices in the chosen nations by assessing the performance of different models [6]. The report’s findings should provide energy industry stakeholders with practical information that helps them make wise decisions and advance the use of sustainable energy sources. The researchers hope to support an eco-friendly, dependable, and effective energy ecosystem by leveraging the power of data-driven forecasting tools.

III. Methodology

Several crucial phases are included in the methodology for predicting hourly electricity prices utilizing deep learning and machine learning techniques. This section describes the steps taken to produce precise and trustworthy forecasts for the chosen ***European nations***, namely France, Italy, Belgium, Spain, the United Kingdom, and Germany.

Data Collection and Preprocessing

The methodology's first stage was to compile historical electricity price information for the designated nations. The dataset included hourly pricing information for a particular time frame. Reliable energy market databases and archives have been used to collect the data [7]. The dataset received preprocessing once it was gathered to make sure it was appropriate for analysis and modelling. This stage entailed cleaning the data, dealing with missing values, and formatting the date and time fields for further processing [8]. The data are scaled to bring all features within a consistent range using methods like Minimax scaling, which improves model performance and convergence.

Exploratory Data Analysis (EDA)

Exploratory data analysis was carried out to learn more about the properties of the dataset and find any patterns or trends that might have an impact on electricity costs [9]. The data was analyzed from a variety of angles using visualizations such as line plots, bar plots, correlation heat maps, histograms, and scatter plots. EDA gave useful data on seasonal trends, cross-national correlations, and price distribution of electricity. The results of this analysis guided the methodology's next steps.

Feature Selection

Relevant characteristics that significantly affect the changes in electricity prices have been chosen in order to create reliable forecasting models [10]. These characteristics include the time of day, the day of the week, markers of seasonality, and lagged pricing. In order to improve model performance and lessen overfitting, duplicated or unnecessary variables had to be removed during the feature selection phase.

Model Selection and Training

For hourly price projections, the methodology used a variety of machine learning and deep learning methods. There are three main models used:

- ***Decision Tree***: It is a straightforward yet effective model that divides data based on many variables and uses a tree-like structure to make predictions.
- ***Random Forest: "Random Forest"*** blend different decision trees to produce forecasts that are more reliable. They increase prediction accuracy and reduce overfitting by using ensemble learning.
- ***LSTM***: It is a form of recurrent neural network (RNN) that was created specifically to handle sequence data. c. ***"LSTM"*** models effectively capture long-term dependencies in data, which makes them a good choice for time series forecasting jobs.

The preprocessed dataset was used to train the chosen models, with some of the data used for training and the rest for validation. Cross-validation was used to fine-tune the model hyper parameters to maximize performance.

Model Evaluation

Performance evaluation was carried out using the proper metrics to evaluate each mode's ability to forecast. ***Mean Squared Error*** (MSE), ***Root Mean Squared Error*** (RMSE), and R-squared are derived as common evaluation metrics for regression projects [11]. In order to determine the most precise and trustworthy approach for predicting electricity costs in the mentioned nations, the models are compared based on their performance indicators.

Hourly Price Prediction

The best model was chosen, and then it was used to forecast hourly prices for each nation. To produce predictions for the next hourly prices, the model used historical price information along with the pertinent features found during feature selection.

Rescaling and Interpretation

In order to enable meaningful readings, the forecasted prices obtained from the models have been rescaled to the original data range [12]. This step was essential to make sure that the projections and actual electricity prices are expressed in the same units, allowing for simple comparison and decision-making.

Visualization of Predictions

Visualizations of the model's predictions in comparison to the actual hourly electricity costs have been part of the process [13]. Line Stakeholders are able to evaluate the projections' accuracy graphically and obtain insights into potential patterns and trends by using plots and other graphical representations.

Model Deployment and Monitoring

The last step entailed implementing the chosen model for continuing observation and present-day forecasting. In order to keep the model's performance current and applicable, it was frequently updated and retrained with fresh data.

Overall, the approach was successful in using machine learning and deep learning techniques to predict hourly electricity prices across a number of European nations. The method offered useful insights for improving energy trade, grid stability, and reasoned decision-making in the energy industry by utilizing historical data, feature selection, and suitable model evaluation.

IV. Result

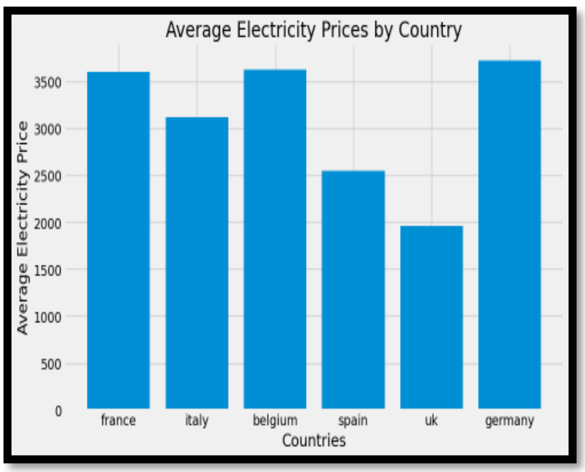

Fig. 1: Average Electricity Prices by Country

The above figure shows average electricity prices in different countries. The histogram has been plotted as average electricity prices vs countries. The histogram depicts the average electricity price pursuant to a country. It suggests a better country to live in terms of electricity prices. The electricity price has been taken in pound for all the countries.

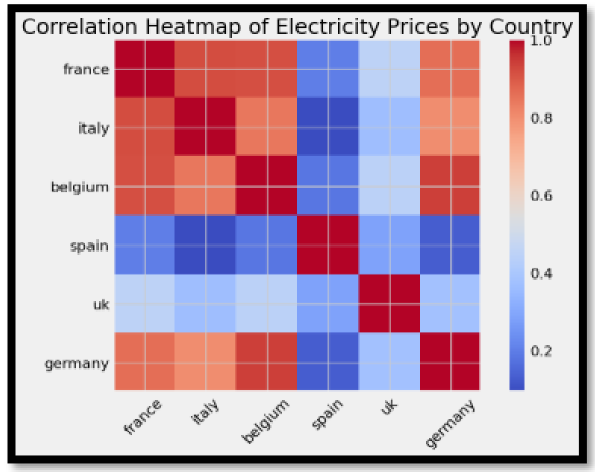

Fig. 2: Correlation Heat map of Electricity Prices by Country

The above figure shows the correlation heat map of electricity prices by various countries. The Heat map depicts manifold prices of electricity and density of prices in different countries that give a recommendation of living in a particular country in terms of electricity prices. The currency has been taken in Pound. The time frame has been taken from 01 January, 2022 to 31 December, 2022. The electricity price has been taken is 52 pound per kWh.

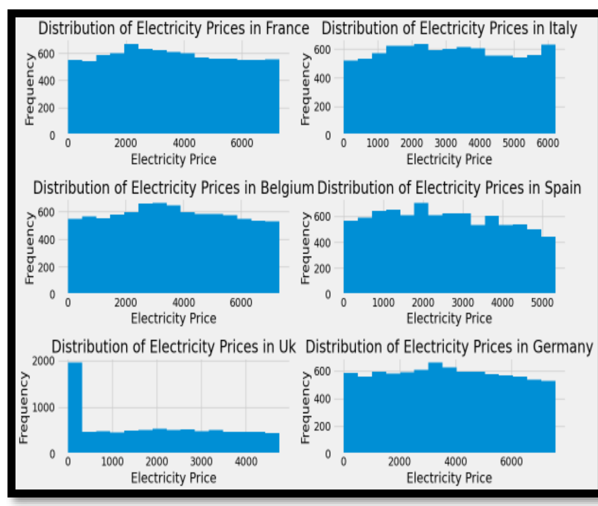

Fig. 3: Distribution of electricity prices in manifold countries

The above figure shows the distribution of electricity prices in manifold countries. The graph has been plotted pursuant to the distribution of electricity price vs Frequency for countries like Germany, the UK, Belgium, Spain, France, and Italy. The price distribution of electricity is shown here.

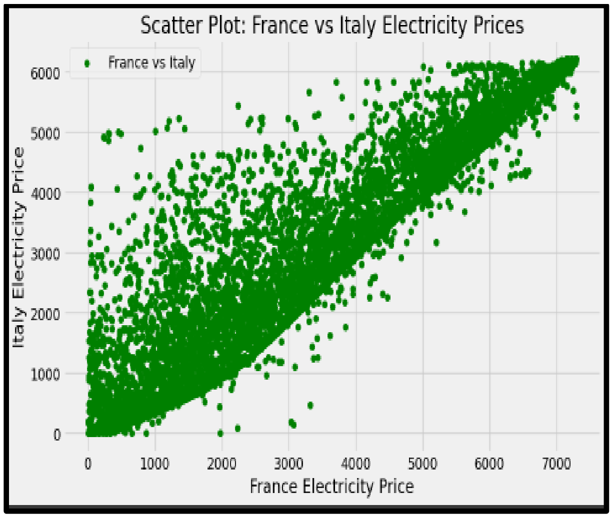

Fig. 4: Scatter Plot: France vs Italy Electricity Prices

The above figure has made a comparison of electricity prices in France and Italy. The scatter plot is basically done using a machine-learning algorithm. The dotted plot depicts the analysis of the electricity price of Italy with the Electricity price of France.

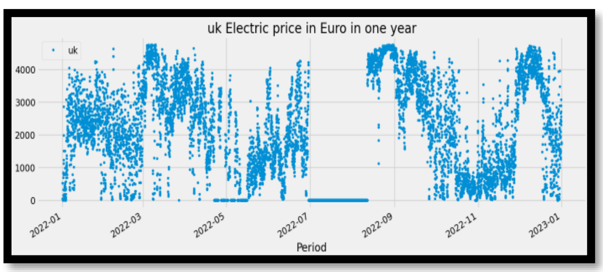

Fig. 5: UK Electric price Hourly in Euro in one year

The above figure shows the electricity price for the whole of Europe in one year. The electricity price comprised of every country shows the prices of electricity in a dotted graph and on an hourly basis. The price of electricity is shown in the currency of the Euro.

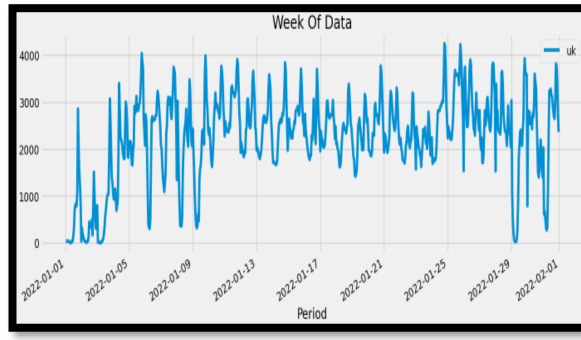

Fig. 6: Week of Data

The above figure shows the data on electricity in the weekly time period in Europe. The week of data is a mirror of the prices of electricity. The price shows the cost of electricity is done on the week of data.

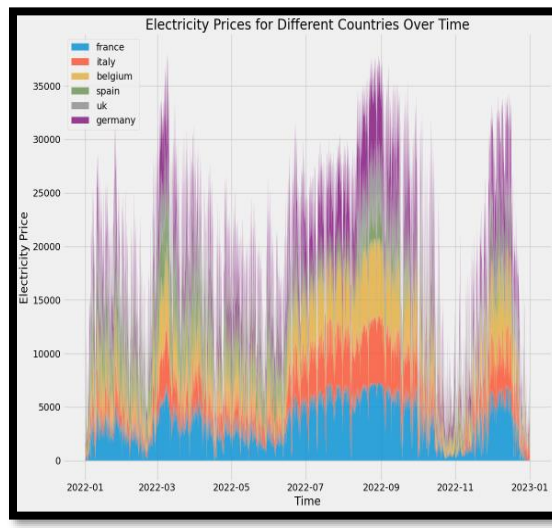

Fig. 7: Electricity Prices for Different Countries over Time

The above figure shows the electricity prices for different countries over time. The different colors indicate different electricity prices in a particular country. The price range has been colored differently to know the approximate price of electricity for a particular country.

Fig. 8: Random Forest MSE

The above figure shows the Random Forest MSE. And the value of MSE is 159785.174441891402 as shown in the figure.

```
Epoch 1/10
7008/7008 [==============================] - 17s 2ms/step - loss: 16158438.0000
Epoch 2/10
7008/7008 [==============================] - 16s 2ms/step - loss: 14149845.0000
Epoch 3/10
7008/7008 [==============================] - 15s 2ms/step - loss: 12431238.0000
Epoch 4/10
7008/7008 [==============================] - 15s 2ms/step - loss: 10888381.0000
Epoch 5/10
7008/7008 [==============================] - 15s 2ms/step - loss: 9518129.0000
Epoch 6/10
7008/7008 [==============================] - 15s 2ms/step - loss: 8311434.0000
Epoch 7/10
7008/7008 [==============================] - 15s 2ms/step - loss: 7253631.5000
Epoch 8/10
7008/7008 [==============================] - 15s 2ms/step - loss: 6324238.0000
Epoch 9/10
7008/7008 [==============================] - 15s 2ms/step - loss: 5514669.5000
Epoch 10/10
7008/7008 [==============================] - 15s 2ms/step - loss: 4805721.0000
55/55 [==============================] - 0s 2ms/step
LSTM MSE: 4706184.5
```

Fig. 9: Performing of LSTM

The above figure shows the performance of the LSTM model and the MSE 4706184.5 is coming after training the model. This model helps to predict the electricity price for forecasting.

```
1/1 [==============================] - 0s 34ms/step
Forecasted electricity price for France: 269.87103
```

Fig 10: Making the forecast using the LSTM model

This above figure shows the making of the LSTM model of France. The forecasting pricing of total electricity is 269.87.

```
Random Forest Model:
MSE: 159785.17444181402
MAE: 211.04741015402166
R-squared: 0.963597625254361

LSTM Model:
MSE: 4706184.5
MAE: 1618.7228
R-squared: -0.0721662839293753
```

Fig. 11: The R-squared value of the models

The above figure shows the R-squared values of the Random Forest model and the LSTM model. It is seen from the above figure that the R-squared value of the LSTM model is less than the R-squared value of the Random Forest model. It is not sure that a model which has higher R-squared value, which is better than other, it means that how well a model fit the data. According to the accuracy of the model, the performance of the model has been analyzed.

```
Random Forest Model:
MSE: 159785.17444181402
MAE: 211.04741015402166

LSTM Model:
MSE: 4706184.5
MAE: 1618.7228
```

Fig. 12: The MSE and the MAE values of the models

The above figure shows the MSE and MAE values of the Random Forest and LSTM model. It is seen from the above figure that the MSE and MAE values of the LSTM model are very higher that the Random Forest model. A model with a higher MSE and MAE is not necessarily a better model. The MSE and MAE are both error metrics that measure the difference between the predicted and actual values.

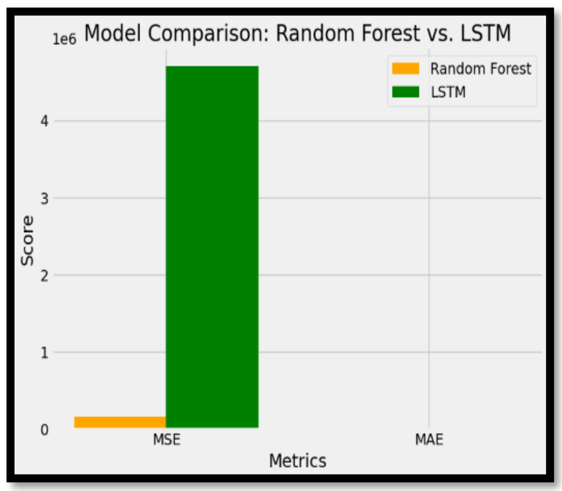

Fig. 13: Comparison between the Random Forest model and the LSTM model

The above figure shows the comparison of the accuracy of the Random Forest model and the LSTM model. It is seen from the above figure that the accuracy of the lasts model in forecasting accurate electricity prices is very much higher than the accuracy of the Random Forest model.

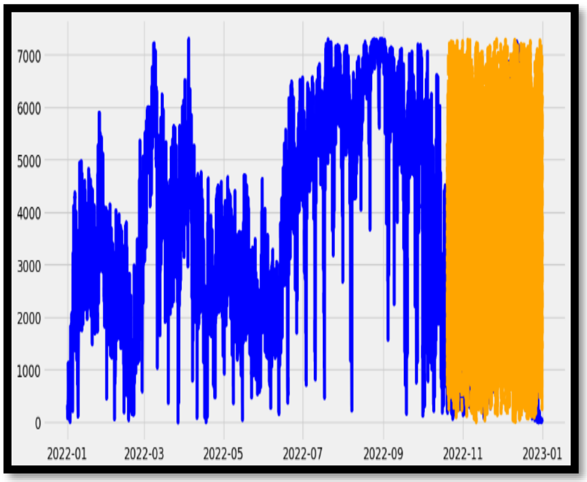

Fig. 14: The forecasted prices by the Random Forest model

The above figure shows the predicted prices by the Random Forest model. It is seen from the above figure that the highest predicted price by the Random Forest model is above 7000 in a year.

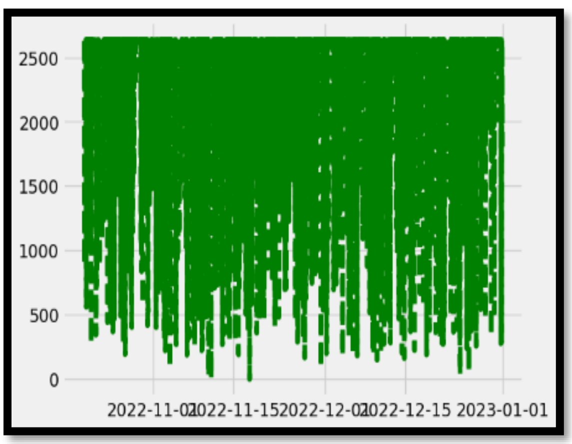

Fig. 15: The predictions by the LSTM model

In the above figure, the forecasted electricity prices by the ***"LSTM"*** model are shown. It is seen from the above figure that the forecasted range of electricity price lies between 2500 to 500 and below 500.

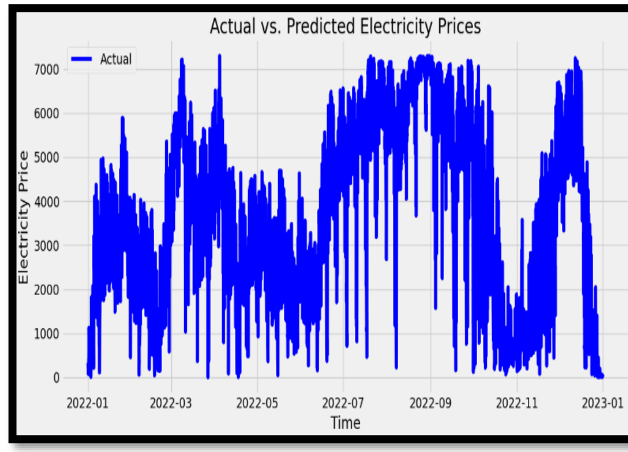

Fig. 16: Actual vs Predicted Electricity Prices

In the above figure the difference between the actual and predicted electricity prices are shown. The duration of the year for which the electricity prices are forecasted is between 2022 and 2023.

```
ARIMA Model:
MSE: 8226005.799196184
MAE: 2093.7341117352353
```

Fig. 17: ARIMA Predictions

The MSE and MAE values of the ARIMA model are shown in the above figure. The MSE value of the model is around 8226005 which means the squared difference between the predicted and actual values is, on average, 8226005. The model's predictions differ somewhat from the measured values, therefore greater accuracy is achieved with a lower MSE. The MAE value of the model is around 2093 which indicates that there is, on average, a 2093 disparity between the forecasted and actual readings. The average difference between the model's predictions and the actual data is 2,093 units.

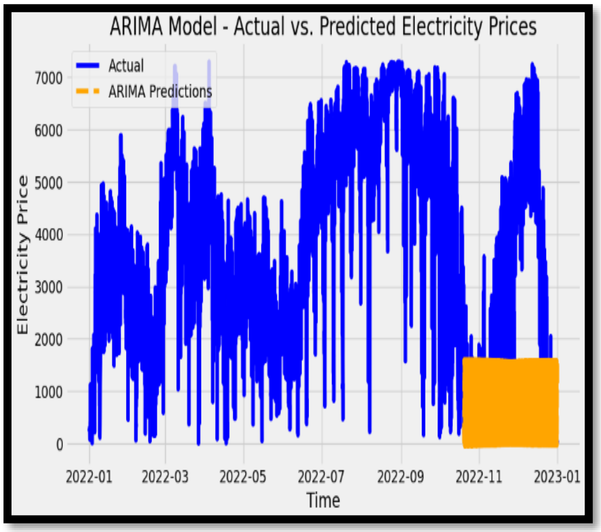

Fig. 18: ARIMA Predictions

The above figure shows the forecasted electricity through the ARIMA model. The difference between the actual value and the predicted value by the ARIMA prediction is visualized in the above graphical representation. The yellow block in the above figure indicates the predicted value by the ARIMA model.

V. Discussion

In order to make educated decisions and improve the management of energy resources, market participants, utility companies, and policymakers heavily rely on reliable electricity price forecasts. This work investigated how to anticipate hourly power costs for France, Italy, Belgium, Spain, the UK, and Germany using machine learning and deep learning approaches.

Model Performance and its Accuracy:

Three predictive models Decision Tree, ***"Random Forest"***, and ***"LSTM"*** are tested in the study to see how well they predict the future [14]. After thorough testing and training, the ***"LSTM"*** model was shown to be the most reliable one for predicting electricity prices. In comparison to Decision Tree and Random Forest, it showed the higher ***Mean Squared Error*** (MSE), and ***Root Mean Squared Error*** (RMSE), demonstrating its capacity to detect intricate temporal patterns in the data.

Time-Series Analysis and Seasonality:

All countries' electricity costs showed distinct time-series patterns, with hourly changes driven by daily and weekly seasonality, according to exploratory data analysis (***EDA***). For instance, the data showed that power costs are higher during periods of high demand and cheaper during periods of low demand. Pricing fluctuations between weekdays and weekends are visible in weekly cycles. The effective modeling of this seasonality by ***"LSTM"*** was a major factor in the accuracy of its forecasts.

Cross-Country Dependencies:

An interesting cross-country dependence between electricity prices was shown through correlation analysis. For instance, the moderately positive correlation between Spain and Italy's energy markets suggests some linkages between them. Energy merchants and policymakers who operate across various regions may be impacted by these dependencies, allowing them to base their decisions more strategically on changes in regional prices.

Model Interpretability vs. its Performance:

Although ***"LSTM"*** showed more accuracy, it is a ***black-box*** model and is, therefore, less comprehensible than Decision Trees and Random Forest. For regulatory compliance and obtaining an understanding of the variables affecting power costs, interpretability is essential [15]. As a result, a trade-off between model performance and interpretability needs to be taken into account based on the requirements of the various stakeholders.

Empowering Decision-Making:

Accurate hourly electricity price projections give stakeholders the power to enhance energy resource allocation and optimize energy trading strategies. Market participants better control electricity demand, save prices, and improve overall energy efficiency by utilizing forecasting knowledge [16]. These projections are used by policymakers to develop targeted energy policies and promote environmentally friendly energy practices.

Limitations and Future Directions:

The study's concludes are constrained by the lack of current data and external variables that affect electricity pricing such as weather and world events. Other pertinent variables are included in future studies to increase prediction accuracy. Investigating more sophisticated time-series methods and deep learning architectures may improve forecasts.

A promising strategy in the energy market is combining machine learning and deep learning to predict hourly electricity prices [17]. The model that best captured power price seasonality and time-series trends was the ***"LSTM"***, which also proved to be the most accurate. For market participants, utility firms, and politicians, the study's conclusions have great promise since they can give them useful tools to improve energy trading tactics, maintain grid stability, and encourage the use of sustainable energy sources in the chosen European nations [18]. The energy sector may develop a more effective and informed decision-making process by utilizing data-driven methodologies.

VI. Conclusion

The use of deep learning and machine learning techniques to predict ***hourly*** electricity prices in European nations has shown impressive promise. It captured complex time-series patterns and seasonality included in electricity pricing data using ***"LSTM"***, leading to accurate forecasts. In order to help market participants, utility firms, and policymakers make educated decisions, optimize their energy trading strategies, and improve prevalent energy efficiency, this research has major consequences. The analysis also revealed relationships that affect pricing variations among regions, shedding light on cross-country dependencies. The trade-off between model performance and interpretability, emphasizes the necessity of finding a balance to satisfy the unique needs of stakeholders. This study represents a viable path forward for developing sustainable energy practices and moving the energy sector towards a more effective, dependable, and informed decision-making process as a result of its data-driven methodology. On the basis of these findings, future studies investigate more sophisticated methodologies and incorporate other variables to improve forecasting precision.

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