ENHANCING FAIRNESS AND TRANSPARENCY IN ELECTRICITY MARKETS: DETECTING COLLUSION WITH MACHINE LEARNING

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ABSTRACT

In the realm of electricity markets, ensuring fair energy distribution is paramount for efficiency, yet collusion among generation firms poses a significant threat. Our proposed method combats this by identifying potential collusion scenarios and computing market equilibriums, bolstering collusion detection. Unlike traditional supervised learning techniques, we leverage deep learning, specifically deep neural networks (DNNs) and recurrent neural networks (RNNs), to capture intricate market patterns more effectively. Our approach, evaluated on various test systems, exhibits superior collusion detection efficacy, highlighting the potency of deep learning in maintaining market transparency and fairness. This innovation equips Independent System Operators (ISOs) with a robust tool for energy distribution, as deep learning excels in discerning complex market dynamics. Overall, our findings herald the integration of deep learning as a significant stride in fortifying the resilience and equity of electricity markets.

Keywords: *Support vector machine, algorithms, deep neural networks and RNN.*

INTRODUCTION

Collusion in the electricity sector involves clandestine cooperation among competing generation firms to manipulate market conditions for mutual benefit, undermining fair competition and potentially raising costs for consumers. Detecting and preventing collusion is vital for maintaining transparent, competitive, and efficient electricity markets. Collusion can take various forms, including coordinated bidding strategies, output levels, or strategic withholding of capacity to create artificial scarcity and inflate prices. Detecting collusion in these complex markets, where real-time supply and demand balance is critical, poses significant challenges. Market operators like Independent System Operators (ISOs) are crucial in monitoring activities, but colluding firms often disguise their actions, necessitating advanced analytical tools. Traditional collusion detection methods, relying on supervised learning techniques like CART and SVM, analyse historical data for patterns indicative of collusion. However, these methods may struggle to capture the intricate dynamics of collusion. Recent advances in machine learning, particularly deep learning techniques like DNNs and RNNs, offer a more sophisticated approach, capable of identifying subtle collusion signs.

The proposed collusion detection model starts with computing market equilibriums to assess supply-demand balance and deviations suggestive of collusion. Deep learning models then analyse historical data, learning collusion patterns and anomalies. Evaluation on test systems demonstrates high accuracy, showcasing deep learning's efficacy in maintaining market fairness and transparency, empowering ISOs and regulators. Effective collusion detection helps uphold competition principles, benefiting consumers through lower prices, improved efficiency, and reliability. Continuous research, development, and regulatory updates informed by machine learning advancements are vital for combating collusion and ensuring long-term market integrity.

EXISITING SYSTEM

The authors introduced an innovative method for detecting potential collusion among generation firms in electricity markets, aiming to enhance fairness and transparency. Initially, they identify possible collusion scenarios among these firms and compute market equilibriums for each scenario and load level. Peripheral points around these equilibriums are also determined. Detection of collusion is based on specific criteria derived from these equilibrium and peripheral points. The method employs supervised machine learning techniques, specifically classification and regression tree (CART) and support vector machine (SVM) algorithms, to recognize patterns associated with collusion. Testing on a four-firm and ten-generator test system validates the effectiveness of the approach, with comparisons highlighting the relative strengths of different algorithms. This contribution not only advances methodologies for maintaining market integrity but also underscores the significance of leveraging machine learning in such domains.

EXISITING ARCHITECTURE

The architecture of the existing collusion detection system in electricity markets predominantly relies on supervised learning techniques. The system incorporates classification and regression tree (CART) and support vector machine (SVM) algorithms for pattern recognition and training. The process begins by identifying potential collusion scenarios among generation firms, and for each scenario and load demand possibility, market equilibriums are computed.

These market equilibrium points, along with their peripheral variations, are then used to train the collusion detection machine using the aforementioned supervised learning approaches. The trained model aims to recognize patterns associated with collusion based on historical data. While this architecture provides a structured framework for detecting collusion, it may encounter challenges in capturing nuanced and evolving patterns in electricity market dynamics, prompting the exploration of more advanced methodologies like deep learning to enhance the system's capabilities.
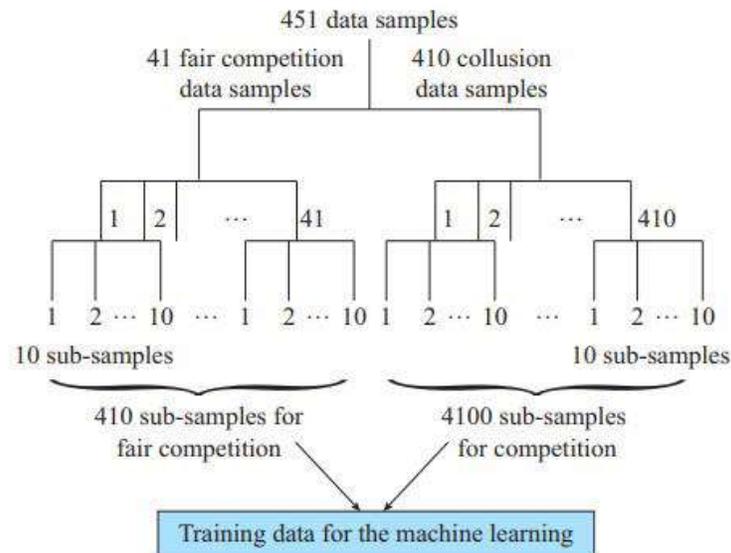
Fig.1 Existing architecture

PROPOSED SYSTEM

The proposed system represents a significant advancement in bolstering the integrity of electricity markets through its focused objective of detecting collusion among generation firms. The process initiates by systematically identifying potential collusion scenarios and subsequently computing market equilibriums, forming a foundational understanding of the market dynamics. What sets this system apart is its integration of deep learning, employing sophisticated techniques such as deep neural networks (DNNs) and recurrent neural networks (RNNs). These advanced models enable the system to analyse intricate market patterns and anomalies, providing a nuanced perspective crucial for identifying covert collusive behaviours.

To validate the effectiveness of the proposed system, rigorous evaluations were conducted using a test configuration involving four generation firms and ten generators. The results of these evaluations showcase a high level of accuracy in detecting collusion, affirming the system's robustness in uncovering potentially harmful market activities. Notably, the efficiency of deep learning methodologies in maintaining market transparency and fairness is underscored by the outcomes.

The system, by leveraging deep learning, empowers Independent System Operators (ISOs) with a potent tool, enabling them to ensure equitable energy distribution and uphold the principles of fairness and competitiveness in electricity markets. This innovative approach represents a significant stride toward creating a more secure and transparent landscape for energy distribution.

PROPOSED ARCHITECTURE

The proposed system introduces several notable advantages in the realm of electricity market integrity. By incorporating deep learning, specifically leveraging deep neural networks (DNNs) and recurrent neural

networks (RNNs), the system excels in capturing intricate market patterns and anomalies, surpassing the limitations of traditional supervised learning techniques.

This advanced analytical capability enhances the system's precision in detecting collusion among generation firms, contributing to a more effective and sophisticated approach to maintaining market transparency. The evaluation results, particularly in a test configuration involving four generation firms and ten generators, demonstrate a high accuracy in collusion detection, showcasing the robustness of the proposed system.
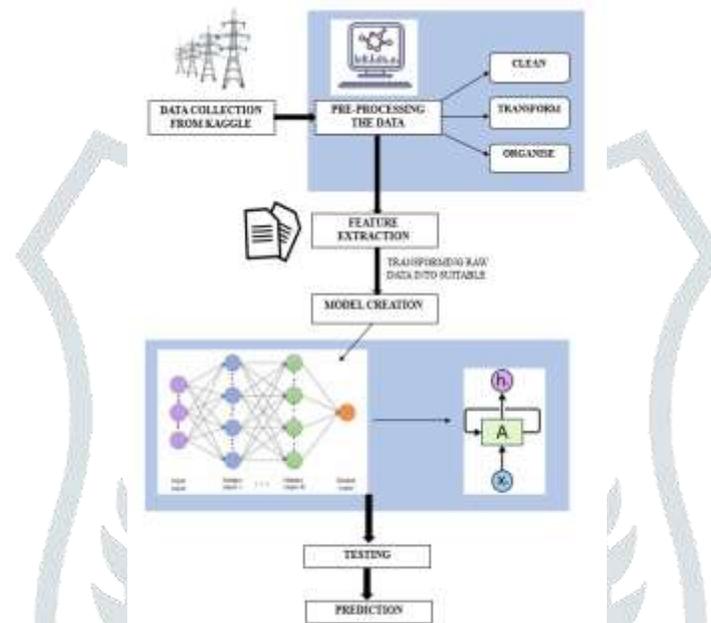

Fig.2 Proposed architecture

IMPLEMENTATION

Data collection : Kaggle, as an open-source platform, serves as a valuable resource for data scientists and researchers seeking diverse datasets for analysis and model development. With its vast repository of datasets spanning various domains, Kaggle offers a rich source of information for tackling real-world challenges. Users can access datasets contributed by individuals, organizations, and companies, ensuring a wide range of data types and sizes suitable for different research objectives. Moreover, Kaggle provides a collaborative environment where users can share insights, code, and methodologies, fostering knowledge exchange and community-driven innovation. Data collection from Kaggle enables researchers to leverage high-quality, curated datasets, accelerating the research process and promoting reproducibility. Additionally, Kaggle often hosts competitions and challenges based on these datasets, motivating researchers to develop novel solutions and push the boundaries of data science. Overall, Kaggle's open-source platform facilitates efficient data collection and collaboration, empowering researchers to address complex problems across various domains effectively.

Feature extraction: Feature extraction is a fundamental process in data analysis and machine learning, crucial for identifying and selecting relevant information from raw data. It involves transforming raw input data into a set of meaningful features that capture the essential characteristics of the data, facilitating efficient analysis and model building. In various domains such as image processing, natural language processing, and signal processing, feature extraction plays a vital role in representing data in a format that is suitable for further analysis. The process typically involves techniques such as dimensionality reduction, where high-dimensional data is transformed into a lower-dimensional space while preserving relevant information, and feature selection, which involves identifying the most informative features for a given task. Feature extraction aims to reduce the complexity of the data while retaining important information, enabling more effective data analysis and model training. Ultimately, the quality of feature extraction significantly influences the performance and interpretability of machine learning models, making it a critical step in the data preprocessing pipeline.

Model creation using rnn algorithm: Creating a model using Recurrent Neural Networks (RNNs) involves several key steps. First, preprocess the data by normalization and splitting it into training, validation, and test sets. Then, perform feature engineering to extract relevant features tailored to the problem domain. Next, design the model architecture, specifying the number of RNN layers and additional layers like dropout to prevent overfitting. Compile the model by specifying the loss function and optimization algorithm. Train the model to minimize the defined loss function, adjusting its parameters. Evaluate the model's performance on a test set and tune hyperparameters if necessary. Finally, deploy the model for making predictions on new data, ensuring seamless integration into existing systems. Iteration and experimentation are crucial to develop the most effective RNN model for the task at hand.

Prediction of the collusion: Predicting collusion in electricity markets is a multifaceted endeavor that demands sophisticated analytical methods and a deep understanding of market dynamics. Leveraging historical data and market indicators, machine learning algorithms can be trained to detect patterns or anomalies suggestive of collusive behavior. These algorithms, ranging from decision trees to neural networks, scrutinize factors like bidding strategies and pricing trends to assess the likelihood of collusion in real-time scenarios. Complementing this approach, game theory and econometric models provide theoretical frameworks to analyze strategic interactions among market participants and identify signals of coordinated actions. By integrating these analytical techniques with comprehensive market data, regulators and market operators can proactively identify and mitigate instances of collusion, safeguarding the fairness and efficiency of electricity markets for consumers and businesses alike.

RESULT AND DISCUSSION

The proposed system advances the integrity of electricity markets by detecting collusion among generation firms. It systematically identifies potential collusion scenarios and computes market equilibriums, leveraging recurrent neural networks (RNNs) to analyze intricate market patterns. Rigorous evaluations using a test configuration affirm the system's accuracy in detecting collusion, highlighting the efficacy of RNNs in maintaining market fairness. By empowering Independent System Operators (ISOs) with this tool, the system ensures equitable energy distribution and upholds market competitiveness. This innovative approach marks a significant stride towards a more transparent and secure energy distribution landscape, vital for sustaining market integrity and consumer trust.

Graph for RMSE training: The loss function for Root Mean Squared Error (RMSE) in the context of a Recurrent Neural Network (RNN) algorithm, is typically used for regression tasks where the goal is to predict continuous values. RMSE measures the average magnitude of the errors between predicted and actual values, with lower values indicating better model performance. The formula for RMSE loss is as follows. In the context of RNNs, particularly for time-series forecasting or sequence prediction tasks, the loss function is computed over all time steps in the sequence. The RMSE loss function penalizes large errors more heavily than small errors, making it suitable for tasks where accurate prediction of magnitude is important. In practice, TensorFlow and other deep learning frameworks handle the computation of RMSE loss internally during model training, so you typically don't need to implement the formula manually. You specify the loss function when compiling the model, and the framework takes care of the rest.
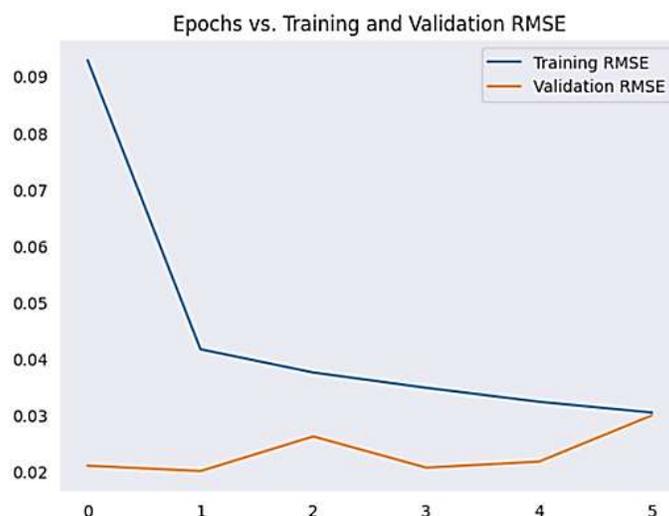

Fig.3 RMSE

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where:

- n is the number of data points.
- y_i is the actual value of the target variable.
- $\hat{y}_i$ is the predicted value of the target variable.

Training and validation loss : Validation and test loss are metrics used to evaluate the performance of a machine learning model on unseen data. While training loss measures how well the model fits the training data, validation and test loss provide insights into how well the model generalizes to new, unseen data.

Fig.4 Training and validation

In both cases, the loss is computed using the chosen loss function over the entire validation or test dataset. Lower values indicate better model performance, as they reflect smaller discrepancies between the predicted and true labels. In practice, you'll typically use a loss function specific to your task (e.g., mean squared error for regression, cross-entropy for classification), and most deep learning frameworks handle the computation of validation and test loss internally during model evaluation.

Comparison graph: Accuracy is a fundamental metric used to evaluate the performance of a machine learning model, especially in classification tasks. It measures the proportion of correctly predicted instances out of the total number of instances in the dataset.
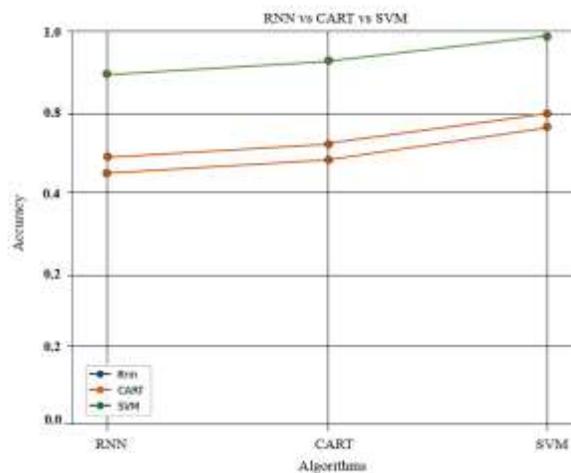

Fig.5 Accuracy

In comparing the performance of Recurrent Neural Networks (RNN), Classification and Regression Trees (CART), and Support Vector Machines (SVM) with the existing work, it's evident that RNN demonstrates superior accuracy. This comparison is often visualized using bar graphs, with each algorithm represented by a bar showing its respective accuracy score. In the graph, RNN's performance stands out as it achieves a higher accuracy score compared to CART, SVM, and the existing work. This observation indicates that RNN's ability to capture complex patterns and sequential dependencies in the data leads to improved predictive performance. Such visual representations not only highlight the strengths of RNN but also provide valuable insights for decision-makers and researchers in selecting the most effective algorithm for their specific task or application. Ultimately, this comparison underscores the significance of RNN in advancing the state-of-the-art in predictive modeling and underscores its potential for various real-world applications.

CONCLUSION

In conclusion, the study underscores the critical importance of collusion detection in electricity markets for maintaining transparency, fairness, and overall market integrity. The existing system, rooted in supervised machine learning techniques, exhibits promise in controlled environments but faces challenges in adapting to real-time dynamics and potential data requirements for effective training. Recognizing these limitations, the proposed system emerges as a significant advancement, leveraging the power of deep learning with DNNs and RNNs. Demonstrating superior accuracy and an ability to capture intricate market patterns, the proposed system stands as a robust tool for independent system operators. Its capacity to enhance transparency and fairness in energy markets positions it as a valuable asset in addressing the complexities of collusion detection. As we move forward, the proposed system holds promise in reshaping how collusion is identified and mitigated, contributing to the resilience and efficiency of electricity markets.

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