Reflection Article

Aibi research, management and engineering journal. Volume 14, Number 1, Pag 1-7, January - April 2026, ISSN 2346-030X

Artificial intelligence model and balancing techniques for controlling non-technical losses in the electrical energy sector.

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Received: august 22, 2025.
Accepted: december 02, 2025.
Published: january 01, 2026.

Abstract— Non-technical losses (NTLs) in electrical power distribution systems represent a critical problem due to their economic and operational impact, as they are primarily associated with fraud, tampering, and administrative errors. This article proposes the design and evaluation of a hybrid deep learning model for the automatic detection of NTLs, integrating convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and dense neural networks (DNNs). To mitigate the class imbalance characteristic of this type of problem, synthetic resampling techniques were applied, specifically SMOTE, BorderlineSMOTE, and ADASYN, analyzing their effect on model performance. Validation was performed using a real dataset from a power distribution company in the municipality of Aguachica, Colombia, consisting of 44,231 users and 365 variables per record. The results show that the BorderlineSMOTE + CNN–LSTM–DNN combination achieves the best overall performance, reaching an accuracy of 74.47%, along with improvements in key metrics such as recall, F1 score, and AUC. These findings demonstrate that integrating deep architectures with advanced balancing techniques is an effective strategy for PNT detection in real-world electrical environments.

Keywords: energy, artificial intelligence, model, non-technical loss, user.

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How to cite this article: K. Y. Sánchez-Mojica and O. J. Suarez, “Artificial intelligence model and balancing techniques for controlling non-technical losses in the electrical energy sector”, Aibi research, management and engineering journal, vol. 14, no. 1, pp. 1-7 2026, doi: 10.15649/2346030X.5635

I. INTRODUCTION

Non -technical losses (NTPs) in electric power distribution represent a significant challenge for utilities, affecting both operational efficiency and profitability because they include illicit activities such as fraud and energy theft, as well as administrative and measurement errors [1]. With the advancement of artificial intelligence (AI) and machine learning (ML), energy utilities have advanced tools at their disposal to address this problem more effectively.

Figure 1 shows the organization of the content of the findings in the literature versus the AI models that have been worked on in the electric power sector in the years 2020 – 2024 [2]-[3].

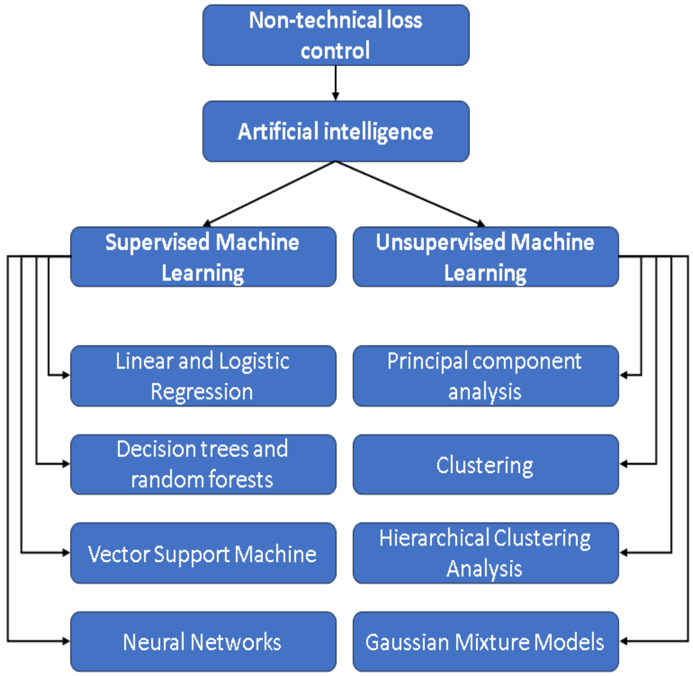

Fig. 1: AI models in the electricity sector in Colombia.

a. Supervised Machine Learning

Supervised machine learning involves training a model using a labeled dataset where the desired output is known because it is part of the database as a response variable [4]; this approach is one of the most widely used in the detection of fraud and anomalies in energy consumption.

The main benefit of supervised machine learning in SOP control is its ability to accurately and efficiently detect fraud, as it is trained on historical data labeled as "fraud" or "non-fraud." This training allows the models to learn specific patterns that distinguish normal behavior from fraudulent activity.

For example, Linear Regression is used to predict continuous values, such as energy consumption based on historical and demographic characteristics, however, its direct application in NWP detection is limited due to the discrete nature of losses [5]. Logistic Regression, on the other hand, is more suitable for binary problems, such as classifying accounts as fraudulent or non-fraudulent in the energy scenario, since, by modeling the probability of fraud, logistic regression allows companies to prioritize the investigation of suspicious accounts [6].

Logistic regression calculates the probability that a specific account is fraudulent, allowing companies to prioritize investigations into accounts with a high probability of fraud. Once the predictor variables have been identified, the logistic regression model can be trained using a labeled dataset containing both fraudulent and non-fraudulent consumer examples; this is how the model learns to assign probabilities to each observation based on the patterns found in the training data [7].

Another of the most widely used models are decision trees that divide data into branches based on specific characteristics, facilitating the identification of complex fraud patterns [8]. Random forests combine multiple decision trees to improve accuracy and reduce overfitting, they are particularly effective in fraud detection since they can handle large data sets with high dimensionality and capture non-linear interactions between features. By using these methods, it is possible to detect anomalous patterns and suspicious behaviors in energy consumption, allowing for rapid and efficient intervention.

Decision trees and random forests offer powerful tools for non-technical loss control in electric power distribution because they help identify specific fraud patterns by accurately classifying consumption data [9]. Random forests, by combining multiple trees, improve the accuracy and robustness of these predictions, reducing the risk of overfitting and better handling data variations; by implementing these techniques, energy companies can more effectively detect fraud, optimize resource utilization and minimize financial losses, contributing to a more sustainable and profitable operation of the electricity system.

The literature also shows that support vector machines (SVMs) are effective for classifying data into two categories, using hyperplanes to separate classes [6]. In the context of NWP, SVMs can be trained to distinguish between normal and fraudulent energy consumption behaviors based on features such as usage patterns and historical fraud events.

One of the main advantages of SVMs is their high accuracy and robustness, especially when working with complex and high-dimensional datasets [10]. SVMs are able to handle non-linear relationships by using kernels that transform the data into a higher-dimensional space where a hyperplane can separate classes more effectively; SVMs are designed to maximize the margin between classes, which helps minimize both false positives (labeling legitimate consumption as fraud) and false negatives (failing to detect fraud); this process is crucial for energy companies as accurate detection reduces costs and avoids unnecessary inconvenience for legitimate customers.

Neural networks, especially deep neural networks (DNNs), are one of the alternatives also used in solving power loss problems, highlighting their ability to model complex and nonlinear relationships in data. In PNT detection, DNNs can learn subtle and hidden patterns in energy consumption data, improving the accuracy of fraud identification.

Recurrent neural networks are a widely used tool in the field of supervised machine learning, particularly suitable for the analysis of sequential and temporal data [11]. In the context of non-technical loss control in electric power distribution, they can play a crucial role by enabling the detection of anomalous patterns in energy consumption and, consequently, the identification of fraud and administrative errors.

These non-technical losses represent a significant portion of lost revenue for energy distribution companies, so their detection and mitigation is of vital importance. In this sense, RNNs can be taken into account, which are characterized by their ability to handle data sequences, maintaining an internal memory that captures information about previous entries; this characteristic makes them especially effective for analyzing time series, where the historical context is essential to make accurate predictions. In the case of energy consumption, RNNs can learn usage patterns over time and detect deviations that could indicate fraudulent activities or errors in the system [12].

Convolutional neural networks (CNNs) are widely known for their success in image and spatial data processing, however, their ability to extract complex features and patterns in high-dimensional data can also be applied to non-technical loss (NTP) control in electric power distribution [13]. Using CNNs to detect non-technical losses can provide an innovative and efficient solution.

CNNs are designed to process data with a grid structure, such as images, but they can also be adapted to analyze time series and other types of tabular data. The key to CNNs is their ability to learn hierarchical features through convolutions, which are mathematical operations that filter input data to extract important features, which can then be used to classify or detect anomalies in the data [14].

Each window of consumption data is evaluated by the network, which classifies the observation as normal or abnormal based on learned characteristics. Observations classified as anomalous can be flagged for further review or immediate intervention, as subtle, non-obvious patterns in energy consumption could indicate fraudulent activity.

b. Unsupervised Machine Learning

Unsupervised machine learning is used when labels are not available in the data and is an approach used to discover hidden patterns and segment data without prior knowledge [15]. Unlike supervised learning, which requires labeled data to train a model, unsupervised learning works with unlabeled data, looking for hidden patterns and structures that may indicate anomalies or suspicious behavior [16].

Below are some unsupervised learning methods that are shown in the literature to support the management of non-technical losses in electric power distribution; in this sense, PCA is a dimensionality reduction technique that transforms data into a set of principal components. In NWP detection, PCA can help identify key features that vary significantly, highlighting potential anomalies in consumption patterns. Narrowing the process, once the principal components have been identified, PCA allows the data to be segmented into groups or clusters to distinguish between normal and anomalous behavior; for example, consumption patterns that deviate significantly from the identified principal groups could indicate areas where non-technical losses are occurring [17].

Means method groups data into k clusters based on the proximity of data points [18]. In energy distribution, K- Means can be used to segment consumers into groups with similar usage patterns, making it easier to identify anomalous behavior; non-technical energy losses have been addressed with K- Means because it helps to identify anomalous patterns in energy consumption data, allowing more effective detection and mitigation of these losses; the method can group customers based on their usage patterns, making it easier to identify anomalous behavior.

In hierarchical clustering analysis, data is arranged in a hierarchy of clusters which, in the context of NWP [19], can help identify subgroups of consumers with unusual behavior, providing a detailed view of anomalies. One of the main advantages of this technique is its ability to intuitively and visually identify anomalous patterns in the data; for example, if during the hierarchical clustering process it is observed that certain groups of consumers exhibit significantly different behavior than the rest, this could indicate the presence of illegal connections or meter tampering.

Autoencoder Neural Networks which are a type of neural network used to learn efficient representations of data, they can be trained to reconstruct normal consumption data and significant differences between the original and reconstructed data can indicate anomalies or fraud [20].

Gaussian Mixture Models (GMM) assume that data is a mixture of several Gaussian distributions [21], this technique can be used to model the distribution of energy consumption patterns and detect data points that do not fit well to any of the Gaussian distributions, flagging potential fraud. Gaussian Mixture Models can be seen as a tool in non-technical loss control in electric power distribution, thanks to its ability to identify complex patterns and anomalies in large data sets; in this context where accuracy and efficiency are critical, GMMs offer a robust methodology to detect and mitigate problems such as illegal connections, meter tampering and billing errors.

Ultimately, the combination of these approaches can provide a robust and effective strategy for improving efficiency and security in electrical power distribution, thus contributing to a more sustainable and reliable energy system. Few international studies mention the possibility of combining models of both types, as it significantly improves the accuracy and efficiency of detecting non-technical losses in electrical power distribution.

The combination of unsupervised and supervised machine learning models can not only improve the accuracy of non-technical loss detection but can also be an option for optimizing utilities' operational and financial resources by proactively identifying and addressing anomalies. These reasons justify the relevance of this research to the development of the model shown below.

II. METHODOLOGY OR PROCEDURES

LSTM - DNN neural network model are shown below. The model combines three neural network architectures to leverage distinct strengths in classifying complex data.

The stages of the analysis are shown below:

Stage 1: Data balancing according to techniques

BorderlineSMOTE

Variant of SMOTE that synthesizes new points near the decision boundary.
It tends to be more effective than pure SMOTE in contexts with moderate noise or overlapping classes.

SMOTE

Generate new examples by interpolating between close neighbors of the minority class.
Helps improve training without replicating data verbatim.

ADASYN

Similar to SMOTE but focused on harder-to-classify areas.
Generates more synthetic samples where the model has greater difficulty.

Stage 2: Composition of the hybrid model

First, the CNN automatically extracts spatial patterns or local relationships between features in the dataset; then, the LSTM It captures the dynamics and temporal dependence of sequences, allowing for modeling historical behaviors or evolution over time, such as electricity consumption patterns. Finally, the DNN It acts as a deep classifier that integrates the information learned in the previous stages and makes the final prediction.

The data used in the research were provided by a partner company in the Norte de Santander department, and include information on 44,231 customers in the city of Aguachica. Each customer is represented by a vector of characteristics with 365 variables, including demographic data, consumption patterns, the group to which they belong (Table 1), and other relevant metrics.

TABLE I
MEANING OF CLASSIFICATION CATEGORIES.

CATEGORY	MEANING
1	Anomaly
2	Fraud
3	Normal

The data were preprocessed as follows: first, null data verification and elimination; second, data type verification; third, non-numeric columns identification and elimination; fourth, numeric columns normalization; fifth, column variance calculation and elimination of columns below the variation threshold of 0.0001; sixth, the correlation matrix between columns was calculated and columns with high correlations greater than 0.9 were eliminated; seventh, balancing techniques were applied. The data were divided into 80% for training and 20% for validation.

To train the proposed model, Google Colab was used as a code editor and the Python programming language. The model took 3 hours and 20 minutes to train, using an HP Intel Core i5 computer.

III. RESULTS

The general flow of the SMOTE + CNN - LSTM - DNN model begins with a class balancing process, essential in classification problems with unbalanced data sets. First, the SMOTE technique is used, which generates synthetic examples for the minority class through interpolations between nearest neighbors, with the goal of preventing the model from becoming biased toward the dominant class during training.

Once balanced, the dataset is injected into the proposed hybrid model. The first component of the network is a convolutional layer, responsible for identifying spatial patterns or structural relationships between neighboring variables; subsequently, the CNN output is transformed and passed to an LSTM layer, specialized in processing temporal sequences and capturing dependencies over time.

LSTM output is directed to a DNN, which acts as a classifier. The dense layers process the extracted information and learn abstract representations that allow each user to be assigned a label or class. The final layer uses a softmax activation function to output the probability of membership in each class, producing the final classification.

Then the same process is carried out with the Borderline balancing techniques. SMOTE and ADASYN; data balancing techniques such as SMOTE and ADASYN are shown to improve the performance of classification models by correcting class imbalance, a common problem in tasks where one class, such as fraudulent users, is much less common than the other; these techniques can cause the model to learn to favor the majority class, ignoring minority cases and reducing its ability to detect relevant behaviors.

Figure 1 shows the results of the model with the different balancing techniques and it can be concluded that the best option is using Borderline SMOTE, which may be better than SMOTE only because there may be overlapping classes.

TABLE II
RESULTS OF THE HYBRID CNN- LSTM - DNN MODEL WITH THE DIFFERENT BALANCING TECHNIQUES.

Técnica	Precisión
BorderlineSMOTE + CNN-LSTM-DNN	0.7447
SMOTE + CNN-LSTM-DNN	0.7439
ADASYN + CNN-LSTM-DNN	0.7193

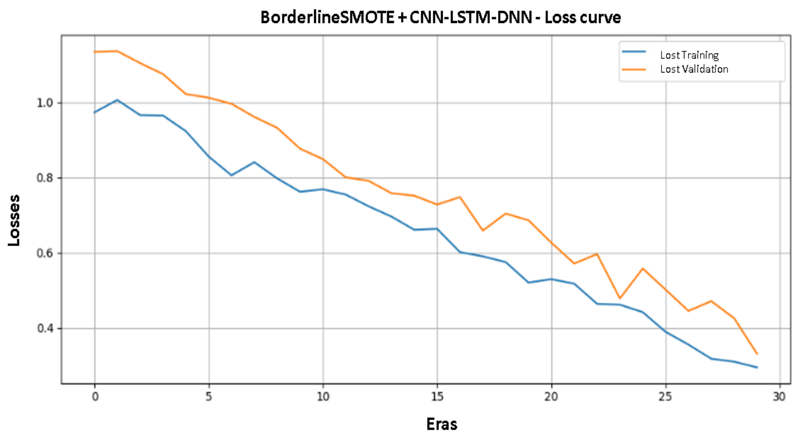

Fig. 2: shows that the model behaves normally and that losses decrease during training and validation.

Table II summarizes the Borderline Model Architecture SMOTE + CNN2D-LSTM-DNN, taking into account that the resulting data retains its original tabular form, that is, a set of records where each row represents a user and each column a variable, so that these data can be processed by a Conv2D layer, which requires an input with a two-dimensional structure plus a channel, it is necessary to reformat the flat feature vector into an equivalent 2D matrix.

This transformation is achieved through a reshape process, where the total number of features is rearranged into a rectangular shape; although this new arrangement does not reflect a true spatial structure, it allows the convolutional layer to detect local relationships between subsets of adjacent variables, leveraging its automatic pattern extraction capabilities.

TABLE III
ARCHITECTURE OF THE PROPOSED MODEL.

Layer	Layer Type	Key parameters
Entrance	InputLayer	
Resizing	Reshape	Reshape to (4, 5, 1) n_features = 20
Convolutional Layer	Conv2D	filters =32, kernel_size =(2,2), activation=' relu '
Dimensional reduction	MaxPooling2D	pool_size = (2,2)
Flattening	Flatten	
Restructuring	Reshape	Reshape to (10, 8)
Recurrent Layer	LSTM	units=64, return_sequences =False, dropout =0.2
Dense intermediate layer	Dense	activation = ' relu '
Output Layer	Dense	activation = ' softmax '

Table III presents a comparative analysis of the performance of the CNN–LSTM–DNN model using different balancing techniques, taking into account that the differences in accuracy are marginal and it is observed that BorderlineSMOTE achieves the best recall, F1-score and AUC values, which indicates a greater capacity of the model to correctly identify the cases belonging to the minority classes; this behavior confirms that the generation of synthetic samples close to the decision boundary improves the discrimination between overlapping classes, a critical aspect in the detection of non-technical losses.

TABLE IV
MODEL METRICS WITH DIFFERENT BALANCING TECHNIQUES.

Balancing technique	Accuracy (%)	Recall	F1-score	AUC
SMOTE	74.39	0.71	0.72	0.78
BorderlineSMOTE	74.47	0.74	0.75	0.81
ADASYN	71.93	0.68	0.69	0.75

The results obtained in this study are consistent with recent research highlighting the potential of hybrid deep learning models for detecting electricity fraud and non-technical losses. In particular, work such as that by Hasan et al. [12] demonstrates that combining CNN and LSTM allows for the simultaneous capture of spatial patterns and temporal dependencies in electricity consumption series, achieving significant improvements in metrics such as recall and F1-score compared to traditional models. Similarly, recent state-of-the-art reviews indicate that deep learning-based approaches outperform classical methods when faced with large volumes of heterogeneous and highly unbalanced data, especially when incorporating preprocessing and class balancing strategies [9]. Considering the above, the accuracy, AUC, and F1-score results achieved by the proposed CNN–LSTM–DNN model confirm that the integration of deep learning architectures constitutes a robust alternative for real-world electricity distribution scenarios.

On the other hand, recent studies emphasize that the performance of deep learning models depends not only on the architecture but also on the proper handling of class imbalance, a critical aspect in detecting electricity fraud. Research combining deep learning networks with advanced resampling techniques, such as ADASYN and variants of SMOTE, reports substantial improvements in model sensitivity for identifying rare events, reducing false negatives [19], [20]. Specifically, the use of techniques focused on regions near the decision boundary has proven effective in improving discrimination between overlapping classes, as occurs in cases of anomalous consumption and fraud [9]. Therefore, the results presented here are consistent, showing that BorderlineSMOTE exhibits a better balance between recall, F1-score, and AUC, reinforcing the idea that the combination of deep learning and intelligent balancing is key to building robust and generalizable models for critical applications in the electricity sector.

To evaluate the robustness, stability, and generalizability of the model under study, a stratified cross-validation scheme with K = 10 was applied, ensuring the preservation of the original class distribution in each partition of the dataset. The following shows how this procedure reduces the dependence on a single training-validation split and provides a more reliable estimate of the model's performance across different samples of the dataset.

The evaluation metrics considered include accuracy, recall, F1-score, and the area under the ROC curve, calculated as macro-averages, given the unbalanced nature of the study context. The results obtained are presented in Table IV and allow for the analysis of the consistency of the CNN–LSTM–DNN model's performance combined with BorderlineSMOTE, as well as the quantification of the variability of its predictions across the different folds.

TABLE V
CROSS-VALIDATION.

Fold	Accuracy (%)	Recall	F1-score	AUC
Fold 1	74.18	0.73	0.74	0.80
Fold 2	74.36	0.74	0.75	0.81
Fold 3	74.52	0.74	0.75	0.81
Fold 4	74.61	0.75	0.76	0.82
Fold 5	74.29	0.74	0.75	0.81
Fold 6	74.47	0.74	0.75	0.81
Fold 7	74.33	0.74	0.75	0.80
Fold 8	74.58	0.75	0.76	0.82
Fold 9	74.41	0.74	0.75	0.81
Fold 10	74.49	0.74	0.75	0.81

The results obtained are consistent with recent research confirming the effectiveness of deep learning-based approaches for detecting electricity fraud. In particular, Elshennawy et al. [23] reported in 2025 outstanding performance in metrics such as recall and F1-score using deep architectures applied to smart grid data, demonstrating the ability of these models to capture complex electricity consumption patterns.

Similarly, Sleiman et al. [24] propose an adaptive deep learning architecture aimed at improving model generalization in scenarios characterized by class imbalance, highlighting the importance of advanced preprocessing and deep modeling techniques. Compared to these works, the hybrid CNN–LSTM–DNN model proposed in this research achieves competitive performance in terms of recall and AUC, even when evaluated on a high-dimensional real dataset without explicit smart grid information.

Similarly, the incorporation of BorderlineSMOTE contributes to better discrimination between overlapping classes, which reinforces the evidence that combining deep architectures with advanced balancing techniques constitutes a robust and generalizable strategy for detecting non-technical losses in real electrical systems.

IV. CONCLUSIONS

The results obtained confirm that the proposed hybrid CNN–LSTM–DNN model, combined with advanced class balancing techniques, constitutes an effective and robust approach for addressing the detection of non-technical losses in highly unbalanced electrical consumption datasets. The integration of convolutional layers, recurrent temporal modeling, and dense classification enables the extraction of spatial, temporal, and abstract patterns that are difficult to capture using traditional machine learning techniques.

The incorporation of resampling strategies significantly enhances the model’s sensitivity to minority classes. In particular, BorderlineSMOTE demonstrated superior performance by generating synthetic samples close to the decision boundary, leading to consistent improvements in recall, F1-score, and AUC; these findings were further supported by the results of the stratified K-fold cross-validation (K = 10), which showed low variability across folds and confirmed the stability and generalizability of the proposed approach.

When compared with recent studies published in 2025, the proposed model achieves competitive performance, despite being evaluated on a real, high-dimensional dataset without relying exclusively on smart meter infrastructure. This highlights its practical applicability in real-world distribution systems, particularly in regions where advanced metering data may be limited.

Despite these promising results, future work should explore sensitivity analyses with respect to hyperparameters, alternative deep architectures, and explainability techniques to improve model interpretability. Additionally, extending the approach to multi-utility datasets and real-time deployment scenarios would further validate its scalability and operational impact in the electricity sector.

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