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Original Article

Machine Learning Based Decision Trees for Energy Meter Inspection in Power Sector

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***Abstract* - *This research paper presents an innovative approach to energy meter inspection within the power sector, leveraging the power of machine learning and decision tree analysis. The study seeks to enhance the accuracy and efficiency of inspections by employing a data-driven methodology. By utilizing decision trees, the model can effectively classify and identify meter anomalies, potential defects, and performance irregularities. The integration of machine learning enables the system to adapt and improve over time, ensuring precise and consistent inspections. The results indicate a significant improvement in inspection outcomes, reducing human error and enhancing the overall quality control process. This approach holds promise for more reliable and efficient energy meter inspections in the power sector, ultimately contributing to improved service quality and energy accountability. The novice Machine Learning approach method based on Decision trees and Random Forests is proposed based on a case study of one of the meter manufacturers in India.*

***Keywords* - *Decision Trees, Machine Learning, Random Forests, Energy meters, Inspection optimization.*

1. Introduction

In the contemporary power sector, the accurate measurement and monitoring of energy consumption are paramount for ensuring fair billing, efficient resource allocation, and overall grid stability. The traditional methods of energy meter inspection often rely on manual processes, which can be time-consuming, error-prone, and costly [1].

However, with the advent of machine learning and data-driven techniques, there is a growing opportunity to revolutionize the inspection of energy meters. This research paper explores the application of machine learning-based decision tree analysis as an innovative solution to optimize the inspection of energy meters in the power sector. By harnessing the power of data and intelligent algorithms, this approach promises to enhance the precision and efficiency of inspections, leading to improved service quality and energy accountability.

The adoption of machine learning in the power sector has gained significant traction in recent years [2]. The integration of machine learning algorithms ensures that inspections become data-driven and adaptive [3]. As more inspection data becomes available, the system can continually improve its accuracy and efficiency. This approach also has the potential to reduce the need for human intervention in routine inspections, allowing human inspectors to focus on more complex cases and anomaly resolution [4].

This is primarily due to its capability to analyze vast datasets, identify patterns, and make informed decisions based on historical and real-time information [5]. The use of decision trees, a fundamental machine learning technique, allows for the creation of interpretable models that can classify and detect anomalies in energy meter data [6]. This approach offers a data-driven alternative to the traditional, manual inspection processes, which are not only time-consuming but also subject to human error [7].

This paper delves into the technical aspects of applying decision trees within the context of energy meter inspection and highlights the potential benefits of this approach. By conducting experiments and analyzing the results, it is aimed to demonstrate the effectiveness of machine learning-based decision tree analysis in improving the quality and reliability of energy meter inspections. Furthermore, it explores how this technology can adapt and learn from new data, ensuring that the inspection process becomes increasingly accurate and responsive over time [8].

The implications of this research are profound, as it offers the power sector a means to transform its quality control procedures and, consequently, enhance overall grid performance. The subsequent sections of the paper will delve into the methodology, experiments, and results, providing an in-depth analysis of the potential of machine learning-based decision trees in the inspection of energy meters, ultimately contributing to the advancement of the power sector's efficiency and accountability. Due to its capability to analyze vast datasets, identify patterns, and make informed decisions based on historical and real-time information fast and accurate. The machine learning approach in the power sector has gained attention from researchers in recent years [9]. Specifically, in the context of energy meter inspection, machine learning is used to automate and augment the inspection process.

Machine learning models, particularly those employing decision trees, are instrumental in this context. Decision trees are constructed based on historical data and enable the system to classify and detect anomalies in energy meter readings. These trees provide a transparent and interpretable framework for decision-making. By utilizing past inspection data, machine learning models can recognize patterns associated with malfunctioning meters, irregular consumption patterns, or tampering attempts.

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The implications of this research are profound, as it offers the power sector a means to transform its quality control procedures and consequently enhance overall grid performance. The subsequent section of this paper provides a detailed analysis of how machine learning is used in the inspection process, along with the methodology, experiments, and results, ultimately contributing to the advancement of the efficiency and accountability of the power sector [10]. These facts are explained with a case study.

The method of Random Sample Testing (RST) is an existing method of meter inspection which is commonly followed by distribution utilities, all over the world. However, it has the limitation that if a random sample drawn is defective and vice versa, the entire test may be incorrect. If these tests are supported by decision trees and random forests, as mentioned in this paper, the accuracy of inspection will be improved. Secondly, the method of RST is time consuming. The method proposed in this paper gives quick conclusions regarding acceptance or rejection.

A decision tree is a widely used machine learning algorithm that serves as a visual and computational representation of a decision-making process. It resembles an inverted tree structure, with the root node at the top, branches representing decisions or choices, and leaves corresponding to outcomes or decisions. Decision trees are particularly useful for classification and regression tasks, making them valuable tools for solving problems in various domains, including data analysis, finance, healthcare, and, as mentioned in this paper, the power sector [11].

The basic overview of how decision trees work is furnished below:

- Root Node: The top node of the tree, also known as the root, represents the initial decision or the starting point of the decision-making process.
- Internal Nodes: Internal nodes are decision points within the tree. They represent choices or conditions based on specific features or attributes of the data. For example, in the context of energy meter inspection, an internal node might represent a decision point like "Is the meter reading consistent with normal usage?"
- Branches: Branches emanate from internal nodes and represent the possible outcomes or decisions resulting from the conditions or choices made at those nodes. Each branch leads to another internal node or a leaf node, depending on the outcome of the condition.
- Leaf Nodes: Leaf nodes, often located at the ends of the branches, represent the outcomes or decisions. In the context of classification, they might indicate the class or category to which an input belongs. In regression, they might represent a predicted value.
- Splitting Criteria: At each internal node, the algorithm uses a splitting criterion to determine how to partition the data into different branches. The choice of criterion depends on the type of problem (classification or regression) and the attributes being considered. Common splitting criteria include Gini impurity, information gain, or mean squared error.

The process of building a decision tree involves recursively partitioning the data based on the selected splitting criteria until a stopping condition is met. Stopping conditions might include reaching a certain depth of the tree, having a minimum number of data points in a leaf, or when the data is perfectly classified or predicted.

Decision trees are attractive for their interpretability, as humans easily understand the tree structure, and they can provide insights into how decisions are made. However, they can be prone to overfitting, where the model becomes overly complex and fits the training data too closely. Techniques like pruning can be applied to mitigate this issue [11]. Thus, decision trees are a valuable tool in machine learning for decision-making and predictive modeling. They are versatile and widely used in a range of applications due to their simplicity and interpretability.

Random Forests are another ensemble machine learning technique that combines multiple decision trees to improve predictive accuracy and reduce overfitting [12]. Each decision tree is trained on a random subset of the data and features, making them diverse. When making predictions, random forests aggregate the outputs of these trees to make a more robust and accurate prediction. They are widely used for classification and regression tasks and are known for their ability to handle complex datasets, handle missing values, and provide insights into feature importance. Random forests are a powerful and versatile tool in the field of machine learning [13]. The random forests are used in this paper to find the total probability of acceptance or rejection in a case study.

2. Inspection of Energy Meters

The manufacturers of Energy Meters deliver the lot to the electrical installations against the purchase order. Before putting these meters in service, the inspection is usually carried out at meter testing laboratories. The experimental setup of the proposed system used for the inspection of the energy meter is shown in Figure 1. The following tests are mainly conducted.

1. Accuracy Test - The meter to be tested is connected in series with the standard reference meter. The error between these two meters is calculated at different conditions, such as full load, half load, no load, etc., at different power factors. If the error is within permissible limits, the meter is accepted for keeping in service. For instance, the meter having a class of accuracy of 0.5 should have accuracy within ± 0.5% with reference to the standard reference meter.
2. Dial Test - When the meter is connected to the load, the blinking LED near the meter display indicates a consumption pattern. The scanner provided in the meter testing laboratory counts the blinking in terms of ‘Pulses per kWh’.
3. Magnetic Field Test - As per meter standard IEC 687, the meter should continue working up to the specified magnetic field (e.g. 2 Tesla). It is tested in the laboratory to see whether the meter can withstand the specified magnetic field.
4. Mechanical Vibrations Test - The meter should be able to withstand mechanical vibrations as mentioned in the standard.
5. Minimum/ Maximum current test - The meter should be able to work properly under the following conditions.

- Minimum current as mentioned in the standard. The minimum current is 0.1% of the base.
- Current, as mentioned in IEC 687. Thus, the 5 Amp meter should work flawlessly at a minimum current of 5 mA.
- The maximum current is mentioned in the standard. As per IEC 687, the maximum current is 200% of the base current. Thus, the 5 Amp meter should work flawlessly at a maximum current of 10 Amp.

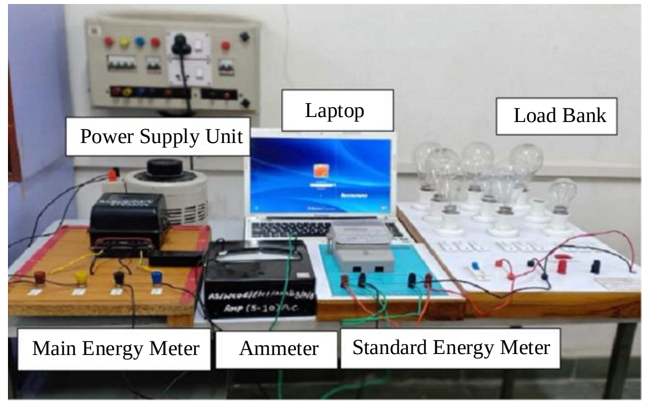

Fig. 1 Experimental set-up of the proposed system used for inspection of energy meter

Figure 1 depicts the laboratory setup to conduct these tests.

3. Formulation of Decision Tree

The formulation of the Decision Tree is based on historical data. This can be understood with a case study of one of the meter manufacturers supplying single phase, 5-30 Amp distribution utility. As per the record received in 2022-23, from the manufacturer shows that out of the 40 meters supplied, 35 meters were accepted and 5 were rejected. Based on this data, the algorithm for acceptance or rejection of meters is developed. First, inspect the first two samples. If both are acceptable, accept the entire lot. Similarly, if both are not acceptable, reject the lot. If one is acceptable and the other is not, draw a third sample. If the third sample is acceptable, accept the lot; otherwise, reject the lot.

Based on the following algorithm, the decision tree is formulated. A Decision tree is a decision-making model in which data is recursively split based on features. It starts with the entire dataset and selects the best feature to split it. This process continues, creating a tree structure. Nodes represent feature conditions, and leaves provide the final decision or prediction. Figure 3 shows the decision tree model for a single phase, 5-30 Amp energy meter supplied by the same meter manufacturer. The algorithm for inspection and acceptance of the lot is given in the Figure 2.

In decision trees, probability plays a significant role in various aspects of classification and regression tasks [14]. It is used to estimate the likelihood of different outcomes. In classification trees, leaf nodes often represent class probabilities, aiding in probabilistic predictions. Probability thresholds can determine binary decisions based on confidence levels.

More advanced decision tree algorithms utilize class probabilities to guide data splits, improving accuracy. When dealing with imbalanced datasets, probabilities help balance class importance. For regression, probabilities may represent prediction uncertainty. Overall, probability in decision trees enhances their versatility by providing not only discrete class labels but also probabilistic insights, calibration, and adaptability for nuanced decision-making [15].

The rule of multiplication in probability states that the probability of two independent events occurring together is equal to the product of their probabilities [16]. In mathematical terms, if A and B are independent events, the probability of both A and B happening is P (A and B) = P (A) * P (B) [17].

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Algorithm: Inspection and Acceptance of a Lot
1. Inspect Sample I
   a. Check the quality or specifications of Sample I
   b. If Sample I is acceptable, go to step 2
2. Inspect Sample II
   a. Check the quality or specifications of Sample II
   b. If Sample I & II are acceptable, go to step 3
   c. If Sample I or II is not acceptable, go to step 4
3. Accept the lot
   a. Output: "Lot accepted."
4. Inspect Sample III
   a. Check the quality or specifications of Sample III
   b. If Sample III is acceptable, go to step 5
   c. If Sample III is not acceptable, reject the lot
   d. Output: "Lot rejected."
5. Accept the lot
   a. If Sample I and Sample III or Sample II and Sample III are acceptable,
      accept the entire lot
   b. Output: "Lot accepted."
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Fig. 2 Algorithm for inspection and acceptance of the lot

Based on Decision Tree analysis, the total probability of acceptance and rejection of single-phase meters is worked out and furnished in Table 1.

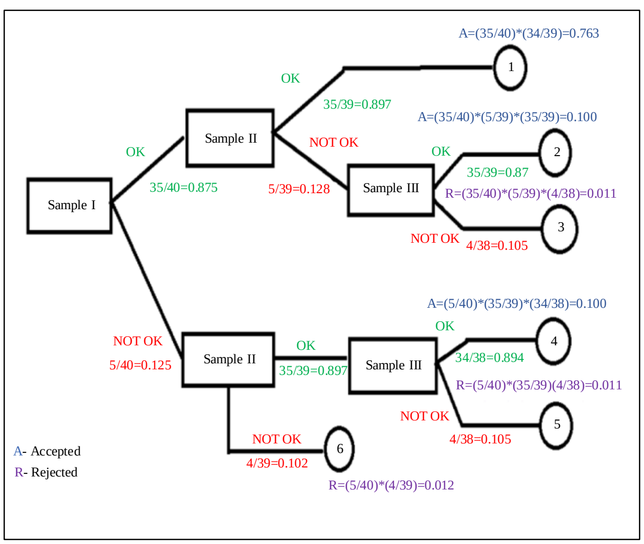

Fig. 3 Decision tree for inspection of single-phase energy meters

Table 1. Probability of acceptance and rejection

Branch	Acceptance	Rejection	Total
1	0.762	0	0.762
2	0.1	0	0.1
3	0	0.012	0.012
4	0.1	0	0.1
5	0	0.012	0.012
6	0	0.012	0.012
Total	0.962	0.036	0.998

4. Formulation of Random Forest

Random Forest is an ensemble learning technique in machine learning. It combines multiple decision trees to make more accurate predictions. It works by creating a multitude of decision trees, each trained on a different subset of the data and using a subset of features. The final prediction is determined by aggregating the results of these individual trees, resulting in improved model accuracy and robustness. In the above example, a random forest with respect to one of the manufacturers of energy meters can be prepared.

Consider that the manufacturer has supplied other meters in addition to single-phase meters, such as three phase, 10-40 Amp meters, prepaid meters, traction meters, Availability-Based Tariff (ABT) meters and Time of Day (ToD) meters. The decision tree of each meter is prepared, and the performance of the manufacturer is evaluated. The combined performance of all decision trees is worked out in Table 2. The data pertaining to the decision trees of other meters is not covered in this paper.

Table 2. Random Forest analysis

Type of Meter	Decision Tree No.	Accepted	Rejected	Total
Single Phase, 5-30Amp Meter	Tree1	0.962	0.036	0.998
Three phase, 10-40Amp Meter	Tree2	0.935	0.064	0.999
Prepaid Meter	Tree3	0.921	0.077	0.998
Traction Meter	Tree4	0.977	0.021	0.998
ABT Meter	Tree5	0.965	0.032	0.997
TOD Meter	Tree6	0.952	0.043	0.995
Total		0.952	0.0455	0.9975

In a manufacturing environment, it is crucial to ensure the quality and reliability of products, especially when it comes to sensitive instruments like meters. To assess the acceptance or rejection of a meter manufacturer, a statistical tool known as a Random Forest model has been employed. This model has revealed that the overall probability of accepting the products from this manufacturer is 95.2%, while the rejection rate is 4.55%.

The Random Forest model is a powerful machine learning technique that can be used for various purposes, including quality control in manufacturing processes. In this case, it has been employed to evaluate the performance of a meter manufacturer. The model analyzes a range of input features and variables associated with the manufacturing process, historical data, and product performance to make a probabilistic determination of whether the meters produced by this manufacturer should be accepted or rejected [16].

The model output indicates that there is a 95.2% probability of accepting the meters manufactured by this company. This high acceptance rate suggests that the products meet the required quality standards and are deemed suitable for use [17].

On the other hand, the rejection rate is reported to be 4.55%. While this rejection rate is relatively low, it still signifies that a small proportion of the products manufactured by this company do not meet the quality standards and must be rejected or subjected to further scrutiny [18].

In view of the above, the use of machine learning models like random forests in manufacturing can greatly improve quality control and decision-making processes [19]. By assessing the acceptance and rejection probabilities, manufacturers can better understand their product quality and make informed decisions regarding whether to accept or reject products [20]. In this specific case, the manufacturer's products have a high probability of acceptance, indicating that most of their meters meet the required quality standards. However, it is essential to continuously monitor and improve manufacturing processes to reduce the rejection rate further. A rejection rate of 4.55% may still result in some level of product waste and rework, which can be costly [21]. Manufacturers can use the insights from the random forest model to identify areas for improvement in their production processes, potentially reducing defects and rejection rates even further [22]. This ultimately leads to increased customer satisfaction and cost savings [23].

5. Conclusion

This research paper delves into the application of machine learning-based decision trees for energy meter inspection in the power sector, with a specific focus on a meter manufacturer producing a diverse range of meters. In this paper, the practical application of machine learning-based decision trees for energy meter inspection within the power sector, with a specific case study focused on a meter manufacturer producing a wide array of meters, including single-phase, three-phase, pre-paid, ABT, ToD, and traction meters, has been explored.

By developing decision trees for each meter type and subsequently constructing a random forest model, valuable insights into the efficacy of this approach have been gained. Through the development of decision trees for each meter type and the creation of a random forest model, we have gained valuable insights into the effectiveness of this approach. The results reveal an impressive overall acceptance rate of 95.2% for meter manufacturers, with a 4.55% rejection rate. Thus, the decision trees and random forests model give accurate and fast results. These findings underscore the potential of machine learning to enhance the quality control and inspection processes in the power sector, ultimately leading to more reliable and efficient energy metering systems.

The success of this research highlights the importance of leveraging advanced technologies like machine learning to improve the accuracy and efficiency of inspection processes, thereby reducing errors, and ensuring the quality of energy meters as compared with other existing methods. As the power sector continues to evolve, embracing such innovative techniques can significantly benefit manufacturers, utilities, and end-users alike. Also, this result serves as a foundation for further advancements in energy meter inspection and quality control, making our power systems more dependable and resilient.

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