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Improving Core Quality in Power Distribution Transformers Using Machine Learning Methods

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Abstract: The estimation of individual core losses of wound core power distribution transformers are particularly important since their core costs account for around 30% of their overall material cost and are one of the key determinants of their quality. In addition, accurate calculations of individual core actual losses are extremely difficult, since actual losses show a divergence of up to 20%, in relation to the theoretical individual core losses. This paper demonstrates the use of Machine Learning (ML) techniques, namely Decision Trees (DTs) and the Learning Vector Quantization (LVQ) neural network to the enhancement of each core's quality in wound core power distribution transformers. The DTs method makes use of inductive inference to automatically build decision rules and apply them to the power distribution transformers production procedure. In the LVQ neural network, any set of input vectors can be classified by using supervised training of competitive layers. Real industrial measurements were used to create the learning and test set. Information includes measurements of the production line's quality control as well as the electrical properties of grain-oriented steel. The resulting DTs present a success rate of 94%. Based on these DTs, rules comprising the most significant parameters and their threshold values can be derived. These are used to lower the actual losses of individual cores, hence raising their quality. The LVQ neural network approach achieves a total classification success rate of 95%.

Keywords: Power distribution transformer, Core quality improvement, Losses, Learning vector quantization, Decision trees

Introduction

Transformer losses in the power distribution network account for a significant portion of all losses (Pamuk, 2022). Distribution transformer iron losses in Turkey are thought to make up to 12% of all distribution network losses (Matiskova & Hrehova, 2021). Predicting iron losses of individual cores is a critical problem in an industrial setting that deals with the transformers with wound cores for distribution built since these losses have a substantial impact on both the quality and functionality of the resulting three-phase power transformers. Additionally, core expenses account for around 30% of the total power transformer material cost (Riemer et al., 2013). In fact, it would be ideal if individual core iron losses could be predicted in the early stages of core production because it would allow for potential corrective steps to be taken while the manufacturing process is still ongoing. It should be noted that the actual individual core iron losses differ from the anticipated iron losses by up to 20%. This is because precise calculations of the iron losses in each core are exceedingly challenging because each core is affected by a variety of qualitative and quantitative characteristics (Pamuk, 2020), (Alatawneh & Pillay, 2012).

The DTs approach and the LVQ neural network are employed in order to investigate the effects of some of these characteristics on unique core iron losses. The DTs approach is a non-parametric learning strategy that can create classifiers for a given problem and is a member of the inductive inference methods (Altayef et al., 2022), (Russell & Norvig, 2015), (Li & Yeh, 2008). Any collection of input vectors can be classified nonlinearly using the LVQ neural network (Melin et al., 2014), (Liu et al., 2010), (Kugler & Lopes, 2007). The information for new, unseen cases is reduced by using the classifiers developed from these two techniques. This research

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presents the use of these two artificial intelligence techniques for enhancing the quality of individual cores. The design of wound core power transformers in fundamental terms, an overview of the DTs methodology and the LVQ neural network, and the application of the two various methodologies for the quality enhancement of individual cores are all covered in the sections that follow.

Projection of Wound Core Quality in Power Distribution Transformers

In order to build the wound core power distribution transformer, the raw material is initially cut into bands of a standard width. After being cut to predetermined lengths, the sheets are coiled around a circular mandrel. The circular core is then compressed into a rectangular shape using the appropriate press. The next step is annealing, which restores the physical and electrical properties of the core (Nie et al., 2016). This is typically accomplished in a protected atmosphere at temperatures between 790 and 880 ^{0}C. (Jardini et al., 2005). Pure, dry nitrogen is the most frequently utilized protective environment because it prevents the steel from oxidizing. Up to 2% of hydrogen may be found in the environment. Four stages make up the annealing cycle used in our application: the beginning and heating up stages (which aim to prevent oxidation and typically achieve a temperature of 815°C), the soaking stage (which aims to ensure that all cores have a uniform temperature distribution), the slow cooling stage (which aims to cool the load slowly in order to prevent the development of internal stresses in the cores), and the fast cooling stage (which aims to reduce the internal stresses) (Nagpal et al., 2006).

The individual cores are divided into two tiny and two large ones that should be used while building a distribution transformer with a wrapped core in three phases. In many cases, F2's width is twice that of F1's. The theory of modest individual core single-phase iron losses, often known as W (1), is presented by:

$$W(1) = WPK_1 * CTW_1 \tag{1}$$

where CTW_1 is the hypothetical tiny core's weight as specified in and WPK_1 is hypothetical with the specified magnetic induction, iron losses particular to each individual core (Awadallah et al., 2015). In Figure 1, the typical loss spider chart is displayed. The huge individual core's hypothetical iron losses, W (2), are as follows:

$$W(2) = WPK_1 * CTW_2 \tag{2}$$

where CTW_1 is the massive core's theoretical weight (Pamuk, 2014).

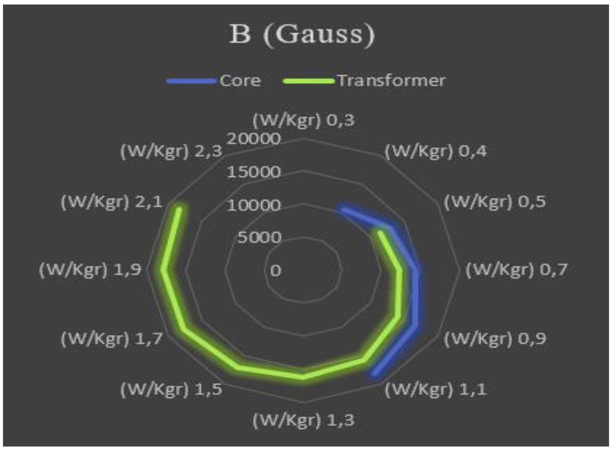

Figure 1. Typical loss spider chart

Decision Trees (DTs) Methodology

The DT is an upside-down tree with a Learning Set as its foundation (LS). The LS consists of a number of pre-classified states that are each defined by a candidate qualification list. Beginning with the entire LS of pre-classified Measurement Sets, at the root node, a DT is first created (MS). The test T that splits these MS "optimally" into the most "pure" subgroups is investigated. A definition of the test T is:

$$T = A_1 \leq t \tag{3}$$

t is the ideal threshold value, while A_1 is the qualification i value for a specific MS. Maximizing the additional information learned from a test determines which test is the best choice. If a node is terminal or "sufficiently" class pure, its classification entropy is compared to a minimal pre-set value $Human_{min}$. It is not further split if it is less than H_{min}, indicating that the node is class-pure enough. These nodes are known as "Limbs." If not, the best splitting rule is used to find an appropriate test to separate the node. The node is labeled a "Blind-Alley" and is not divided if no test can be identified that provides a statistically significant knowledge gain. Test sets (TS), which are collections of related, pre-classified, but separate MS, are used to evaluate DTs. Applying the tests of the various non-terminal nodes allows us to compare the classes of each of these MS to the classes that the terminal node ultimately leads to. This comparison reveals the degree of success of the DT categorization.

Learning Vector Quantization Neural Network Architecture

The input space is divided into several unique regions by the learning vector quantization process, and each zone is identified by representative vectors (Nova & Estevez, 2014). The two tiers of an LVQ network. Figure 2 depicts the LVQ's architecture, including R inputs, S1 competitive neurons, and S2 linear neurons. It shows the competitive transfer function as well as the linear transfer function using CTF and LTF, respectively. The competitive layer, which is the initial layer, uses the Kohonen rule to categorize input vectors according to the "winner-take-all" logic (Kohonen, 2012). The winning cutting-edge neuron creates a2(1) when its weight vector matches the input vector closest using the Euclidean distance measure. Up to S1 subclasses can be learned by the competitive layer because it has one neuron per class.

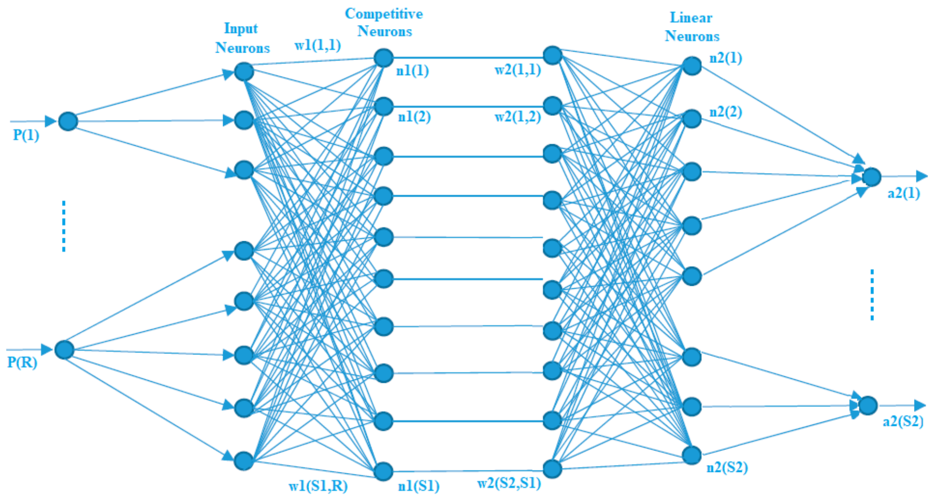

Figure 2. LVQ neural network architecture

Competition in the layer classes is transformed into user-defined S2 goal categories (vector a2) by the linear (second) layer. Using the network targets a2 and the linear layer weights w2, the aim vector a2(l) for the cutting-edge layer is calculated as follows:

$$a2(1) = w2^T * a2 \tag{4}$$

When a competitive neuron i wins and its target is 1, the Kohonen rule is solely applied to adjust the measurements of that neuron. As a result, a successful neuron weights only shift in favor of the input vector if it belongs to the current target class (Hammer et al., 2014):

$$\Delta w1(i, j) = I_r * a1(i) * (p(j) - w1(i, j)) \tag{5}$$

I_r in the above equation represents the process learning rate. However, the Kohonen rule is implemented with a sign change if the victorious neuron belongs to a subclass of a class different than the present target class. The weights of the successful neurons are shifted away from the input vector as a result:

$$\Delta w1(i,\, j) = -I_r * a1(i) * (\, p(\, j) - w1(i,\, j)) \tag{6}$$

So, the LVQ-NN algorithm may categorize any set of input vectors in a non-linear manner, not simply sets that can be linearly separated.

Grading of Core Certain Iron Losses

Establishing the Knowledge Base

The enhancement of individual core quality is the goal. In particular, the quality of the magnetic substance in the core and the impact of the annealing cycle are considered as input factors, as is the difference between the core weight's theoretical and real values. The identical 230 kVA distribution power transformer design and core magnetic material supplier were used throughout all testing. It was made of M3, 0.23 mm, magnetic material. Table 1 displays the design criteria for the 230-kVA distribution transformer. According to the annealing procedure, six requirements have been looked into in Table 2.

Table 1. Design parameter for the 230-kVA distribution transformer

Parameter Names	Values
Rated power	230 kVA
Voltages	20-15/0.4 kV
Connection	Dyn11
Coil material	Copper
Frequency	50 Hz
Type of low voltage coil	Foil
Type of high voltage coil	Wire
Turns of low voltage coil	31
Rated magnetic induction	15200 Gauss
Type of magnetic material	M3
Thickness of magnetic material	0.23 mm
Theoretical weight of small core	65 Kg
Theoretical weight of large core	74.5 Kg
Theoretical losses of small core	46.8 Watt
Theoretical losses of large core	53.6 Watt
Leg thickness at the core	60.2 mm
Width of the main leg	190 mm
Size of the core window	230 mm
Width of window of small core	63 mm
Width of window of large core	120 mm

Table 2. Annealing qualifications

Symbol	Description	High	Low
QUALIF1	Annealing final temperature	855 ^{0}C	825 ^{0}C
QUALIF2	Rising temperature period	4 hours	3 hours
QUALIF3	Temperature of the furnace's opening	350 ^{0}C	250 ^{0}C
QUALIF4	Length of time at a certain temperature	3 hours	2 hours
QUALIF5	Arrangement of the core in the furnace	Up	Down
QUALIF6	Protective environment	98% N_2 & 2% H_2	100% N_2

Table 3. The various annealing tests' conditions

Symbol	Annealing test number							
	1	2	3	4	5	6	7	8
QUALIF1	High	High	High	Low	High	High	High	Low
QUALIF2	Low	High	High	High	High	High	Low	Low
QUALIF3	Low	Low	Low	Low	Low	Low	High	High
QUALIF4	Low	Low	High	High	Low	Low	Low	High
QUALIF5	High	Low	High	Low	High	High	High	Low
QUALIF6	Low	High	High	High	Low	Low	Low	Low

32 experiments are needed to account for all possible combinations with two values for each of the six requirements Low and High. The SDE method can be used to reduce the number of implemented experiments because using all combinations requires a lot of time and money. By using this technique, the necessary number of experiments for my study is reduced to 8. Table 3 displays the characteristics of each of the 8 tests.

It is clear from the symmetrical feature that only four tests are done with each qualification at its lowest value while the other four are run at its highest value. According to SDE, numerous factors can be changed simultaneously and in a methodical way, ensuring the accuracy and independence of the research into the effects and interactions of all the significant components in the production process. A total of 96 cores (48 small and 48 large) were built for each of the eight tests. It should be noted that the same furnace was used to anneal all of the cores. The real-world to hypothetical core weight ratio (QUALIF7) and the particular losses of the core magnetic material are two additional considerations (QUALIF8). The core measurements for one small and one large core are shown in Table 4 as an arithmetic illustration for these requirements.

Table 4. Actual measurements for one small and one large core

Parameter Names	Small Core	Large Core
Annealing test number	4	5
Actual weight (Kg)	65.4	74
Material specific losses (Watt/Kg)	0.72	0.70
Single phase losses (Watt)	54.3	55.3

These qualifications can be assessed using equation 7 for the small core.

$$QUALIF7 = \frac{65.4Kg}{65Kg} = 1.006$$
$$QUALIF8 = 0.72\frac{Watt}{Kg} \tag{7}$$

The values of the qualifications for the two cores under consideration are shown in Table 5.

Table 5. Qualifications for the small and large cores considered

Symbol	Small Core	Large Core
QUALIF1	825 ^{0}C	825 ^{0}C
QUALIF2	4 hours	4 hours
QUALIF3	250 ^{0}C	350 ^{0}C
QUALIF4	3 hours	2 hours
QUALIF5	Down	Up
QUALIF6	98% N_2 & 2% H_2	100% N_2
QUALIF7	1.006	0.993
QUALIF8	0.72 Watt/Kg	0.70 Watt/Kg

Comparing the particular actual losses of iron to the theoretically projected particular iron losses is the basis for defining core iron losses as unacceptable, if the parameter "Ratio" is defined as in equation 8."

Ratio = (Actual Specific Iron Losses of Core) / (Theoretical Specific Iron Losses of Core) (8)

$$RATIO_1 = \frac{\frac{54.3Watt}{65.4Kg}}{\frac{46.8Watt}{65.0Kg}} = 1.153, \quad SmallCore$$
$$RATIO_2 = \frac{\frac{55.3Watt}{74.0Kg}}{\frac{53.6Watt}{74.5Kg}} = 1.039, \quad L\arg eCore \tag{9}$$

If "Ratio" exceeds "Limit," one core is unacceptable; otherwise, it is acceptable. The acceptance limit is indicated by the parameter "Limit," which primarily depends on the needs of the customer. For the core construction described in Tables 4 and Table 5, the parameter "Ratio" for the small and large core is defined as in equation 9 respectively. The little core under consideration is labeled as unacceptable if the parameter "Limit" is set to 1,15, whereas the large core is categorized as acceptable. The percentage of accepted cores per annealing test is displayed in Table 6. For the purpose of creating the learning and test sets, 768 samples were gathered. The remaining 3/4 (576) were utilized as a test set and the remaining 192 as a learning set.

Table 6. Number (%) of approved cores for each test

Percentage	Annealing test number							
	1	2	3	4	5	6	7	8
(%)	94	95	93	69	94	98	98	93

The Outcomes of the DTs Methodology

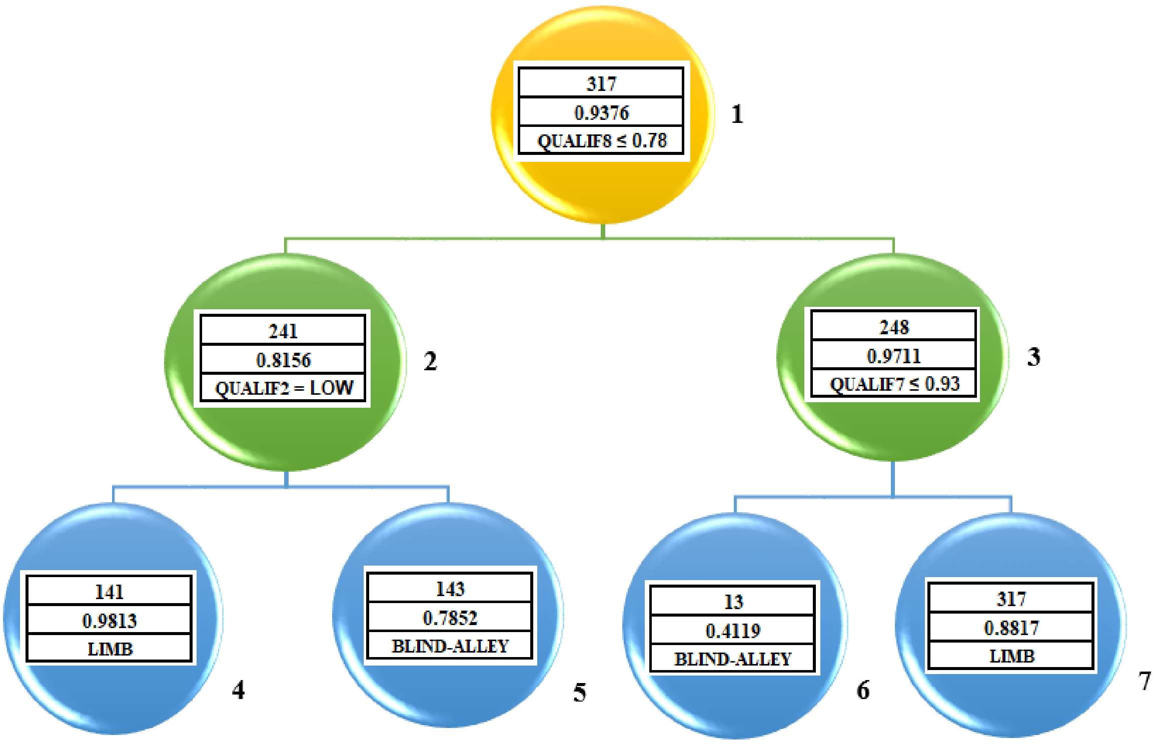

Figure 3. DT was improved using the 8-qualification level

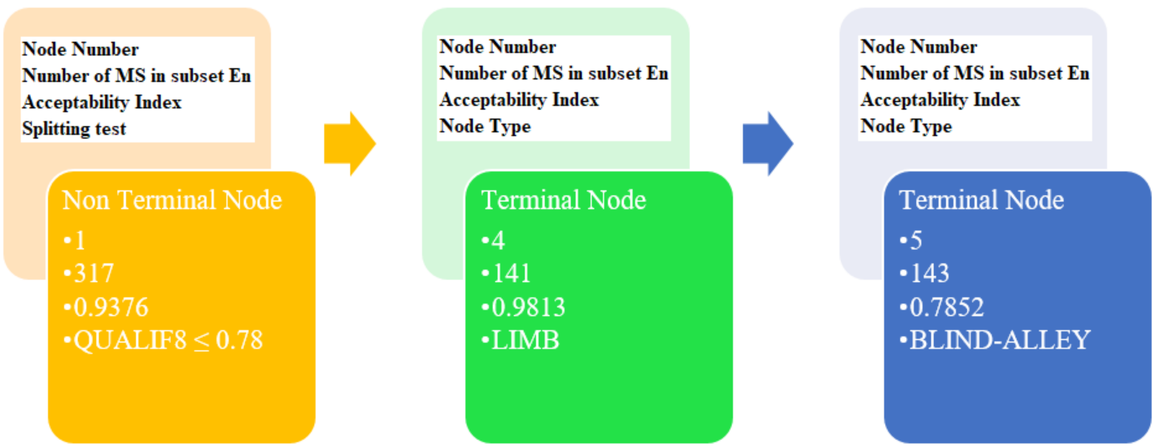

Figure 4. Notes on the nodes of the DTs

In Figure 3 characteristic DTs are shown, improved with the 8-qualification list and 0.986 assurance degree. When measured against the TS comprising 192 MS is 94%. Figure 4 explains the notation that is applied to DT nodes. A node's acceptability index is defined as the proportion of the acceptable MS in the node *n* subset E_n to the total MS in E_n. The MS “dropping” to a terminal node is classified as acceptable if its acceptability index is more than 0.5, and unacceptable otherwise.

The three qualifications that show up when the DT performed its node splitting tests in Figure 3 are QUALIF8, QUALIF2, and QUALIF7, in decreasing order of relevance. The coefficient QUALIF8 reveals the level of the substance since it is equivalent to the particular in the core magnetic material losses. The coefficient QUALIF2 denotes the time at which the temperature rises throughout the annealing cycle, whereas coefficient QUALIF7 the ratio of actual to theoretical core weight is expressed.

Given that each qualification is linked to the caliber of the individual core, their selection is logical and expected. It is noteworthy that QUALIF2 is the only variable that is pertinent to the tempering cycle and occurs in the DT's node splitting tests. This is because QUALIF4, QUALIF5, and the length of the stages of gradual and rapid cooling are all substantially connected, even though the tempering cycle's duration is thought to be constant. However, QUALIF7, which states where the core is located in the furnace, is not significant. Rules that are helpful to the production department are generated from the DTs of Figure 3. If it is technically and financially viable, nodes 4 and 7's connecting cores should be built. The acceptance indices for these nodes are higher than 93%. The measurement sets classified as unacceptable are those that follow the rules QUALIF8>0.78 and QUALIF70.88 and are led to node 6. The production division must raise QUALIF7 to prevent this. This is similar to adding more magnetic material to the core to make it heavier in real terms in order for the simulated core weight ratio (QUALIF7) to be greater than 0.88. The best annealing test can be chosen based on the magnetic material's quality (QUALIF8) as follows:

- The annealing test number 7 must be chosen if QUALIF8≤0.7. The explanation for this is that leading to node 4 in this situation is good. The QUALIF2 requirement can be deduced from the node 2 splitting rule. Additionally, it is clear from Table 6 that tests 6 and 7's annealing cycles are the best because they result in 98% acceptable cores. Only Test 7 of these two tests has a QUALIF2 that is equal to low. This outcome looks odd at first glance. However, if the entire annealing cycle is considered, this can be explained. This comprises the period of constant temperature as well as the phases of slow and rapid cooling. It also includes the time the temperature rises.
- Any one of the eight annealing tests may be chosen if QUALIF8>0.7. The explanation is that the annealing variables have no effect on the node 3 splitting rule.

Results Obtained Using the LVQ-NN Methodology

With the help of the neural network toolbox in MATLAB, the LVQ training algorithm simulator was developed. Considering the size of the LS and TS parameters as parameters that can be provided and changed interactively, "Limit" values were calculated and the number of candidate requirements was increased to 8. This includes the number, learning rate, and the number of competitive neurons in the allowed presentations and target vectors. The test set's categorization results, as determined by the LVQ neural network, are shown in table 7.

Table 7. LVQ-NN classification results

Limit Values	Competitive Neurons	Classification Success Rate
1.05	12	87.2%
1.08	12	90.8%
1.10	15	91.9%
1.12	18	93.3%
1.15	18	95.0%

When the classes are combined, a lower classification success rate is seen (for example, when “Limit” is 1.05, 61.7% of the MS are acceptable while the remaining are not). The classification success rate is equal to 95% if the “Limit” is set equal to 1.15 (the value considered for the DTs creation). It is demonstrated that the LVQ-NN technique is ideally suited for the categorization of precise iron losses to each particular core given the knowledge base employed and the candidate qualification sets chosen. The thresholds of the important features that could be exploited to enhance core quality are not, however, indicated by this method.

Conclusions

For the classification of precise iron losses to each particular core, the DT_S and the LVQ neural network are used in this study. The basic steps for applying the approach are explained, including building the knowledge base, selecting the requirements for candidates, and determining the proper DTS and neural network topologies. The resulting DT has an accuracy rate for classification of 94%, whereas the LVQ-NN structure has an accuracy rate for classification of 95%. On the basis of this DT, guidelines on the core's real weight that are helpful to the production department are derived. Additionally, the best annealing test can be chosen based on the magnet's composition and quality. By lowering their real losses, these two different artificial intelligence techniques are used to improve the quality of individual cores.

Scientific Ethics Declaration

The author declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the author.

Acknowledgements or Notes

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