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Effective use of magnetic materials in transformer manufacturing

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Abstract

This paper has a twofold objective: (a) optimizing the production process of individual cores using Taguchi methods, and (b) reducing the iron losses of assembled transformers, using neural networks. More specifically, we demonstrate the ability of the Taguchi technique accurately to characterize and successfully to optimize the transformer core production process with the minimum of experiments. Moreover, neural networks have been applied to predict iron losses of wound core distribution transformers at the early stages of core construction. The intelligent iron loss model is on-line applied in order to optimally combine the individual cores so that the iron losses of assembled transformers is reduced.

Keywords: Iron; Transformer; Taguchi methods

1. Introduction

High quality products and processes at low cost have become the key to survival in today's global economy. Driven by the need to compete on cost and performance, many quality conscious organizations are increasingly focusing on the optimization of product design. In industrial environment dealing with distribution transformer construction, iron losses constitute one of the most important parameters of transformer quality. In case of wound core type transformers, iron losses of individual cores significantly influence the quality (iron losses) of the assembled transformer.

Typically, iron losses depend upon the grade of steel, its thickness, current frequency, magnetic flux density and weight. These factors are taken into account during the transformer design stage. A number of additional factors affect iron losses during manufacturing, such as the kind of lamination insulation, annealing, core construction, quality of assembly, etc. However, it is not possible to consider all these factors analytically and, therefore, the calculations are traditionally based on graphs and tables obtained from past measurements on actual transformers.

Our paper has a twofold objective: (a) optimizing the production process of individual cores, and (b) reducing the iron losses of assembled transformers. To achieve these targets, Taguchi methods and artificial intelligence techniques are used, respectively.

More specifically, in this paper we demonstrate the ability of the Taguchi technique accurately to characterize and successfully to optimize the transformer core production process with the minimum of experiments, provided one uses statistical techniques, which can ensure valid, and definitive results. In particular, Taguchi methods are applied in order to optimize the annealing process of cores, taking into account the technical characteristics of today's core materials and core designs, parameters very important, if the evolution of standards and materials is considered. Results from the application of the optimal conditions in the production process of magnetic cores demonstrate the feasibility of this method, since it helps reducing core losses as well as the variability of losses and the divergence of actual core losses from the theoretical ones.

Concerning the second objective, it should be mentioned that there is no simple relationship among the parameters involved in the production process that expresses analytically the transformer iron losses. Artificial neural networks have the ability to automatically learn relationships between inputs and outputs independently of the size and complexity of the problem. Neural networks have been therefore applied to iron loss prediction. The intelligent iron loss model (i.e., the model of iron losses obtained through the neural network) is on-line applied in order to optimally combine the individual cores, so that to reduce the iron losses of assembled transformers.

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2. Optimization of core production process using Taguchi methods

2.1. The Taguchi technique

There are two main aspects to the Taguchi technique [1,2]:

1. The behavior of a product or process is characterized in terms of factors (parameters), which are separated into two types: *controllable or design factors, and uncontrollable or noise* factors. The values of design factors may be set or easily adjusted by the engineer or process engineer, while the noise factors are "sources of variation" often associated with the production or operational environment.
2. The controllable factors are divided into those that affect the average levels of the response of interest, referred to as target control factors or signal factors, and those that affect the variability in the response, called *variability control* factors.

The objective of the Taguchi method is to identify the "optimal" settings of the controllable factors, not only to improve the product or process, but also to reduce the influence of the noise factors.

For designing the experiments, Taguchi recommends the use of "orthogonal arrays"; such designs allow the factors to have different numbers of test settings (levels) and also have the pairwise balancing property: every level of a factor occurs with every level of any of the other factors the same number of times. "Fractional" orthogonal arrays minimize the number of trial runs while keeping the pairwise balancing property [3].

The results of the experimental trials are used to compute statistical performance measures, which quantify quality. An analysis of the noise performance measure (NPM), which is a measure of the process variability, will identify the variability control factors and also their optimal combined setting which could minimize this variability. Also, an analysis of the target performance measure (TPM), which is a measure of the process mean, will reveal which of the controllable factors, that are not variability control factors, have a large effect on the mean response — the target control factors; these can subsequently be used to bring the mean response onto the target value.

An outline of the exploratory steps that we have to take using the available data, so that a proper statistical application of the Taguchi technique can be assured, can be found in [4]. An evaluation and a critique of alternative techniques to fractional experimentation and analysis, in particular to those recommended by Dorian Shainin, can be found in [5].

2.2. The experimental design

In our application, Taguchi methods are applied in order to optimize the annealing process of cores. Five controllable variables were identified as potentially important:

PRA: protective atmosphere (% content of H_2 in the mixture of N_2 and H_2);
DCT: duration of constant temperature (in h);
TRT: temperature rising time (in h);
AFT: annealing final temperature (in °C);
FOT: furnace opening temperature (in °C).

Table 1
Controllable variables and their levels

Factor	Levels	
	1	2
PRA	2% H_2 (and 98% N_2)	0% H_2 (and 100% N_2)
DCT	2 h	3 h
TRT	3 h	4 h
AFT	825°C	855°C
FOT	250°C	350°C

For each of the controllable variables two possible levels were considered, as shown in Table 1. The five variables were assigned to the OA_8 orthogonal design. This is a fractional and efficient design for dealing with up to seven two-level factors using only eight experimental trials.

All tests were done using the same 160 kVA transformer design and the same supplier of core magnetic material. The magnetic steel was of grade M3, according to USA AISI, 1983, with thickness 0.23 mm. For every one of the eight experimental trials of OA_8 orthogonal design, 96 (48 small and 48 large) individual cores were constructed. According to this experimental design, 768 measurements were collected in total. It should be noticed that all cores were annealed at the same furnace. For each of the 768 measurements, the values of the factors PRA to FOT, the position of the core in the furnace, the theoretical and actual weight of core, and the theoretical and actual core losses were kept.

2.3. Results

Based on the analysis of the experimental data, the duration of constant temperature and the position of core in the furnace are not statistically significant factors for the core losses.

The most significant factors for the core losses and for the divergence between theoretical and actual core losses are primarily the weight of core and the protective atmosphere, and to lower extent, the temperature rising time, the furnace opening temperature and the annealing final temperature.

The method suggested by Taguchi (i.e., analysis of NPM and TPM) is used in order to find out the factors and their settings that optimize the core production process.

The main conclusions are the following:

1. In order to systematically have low core losses and low divergence between theoretical and actual core losses, as well as the smaller possible influence of noise factors,

the overall optimum process setting is (PRA, DCT, TRT, AFT, FOT) = (0% H_2, 2 h, 3 h, 855°C, 350°C).

2. The core weight significantly affects results. This influence is positive for the core losses (smaller weights, smaller losses) but negative for the core loss divergence (smaller weights, larger divergence).

Results from the application of the optimal conditions in the production process of magnetic cores demonstrate the feasibility of the Taguchi method. In particular, in all the different cases examined, the improvement (reduction) in core losses is between 2.7 and 3.1%. This is viewed as a significant process improvement in an area where even a 1% core loss reduction is considered of paramount importance. Furthermore, the improvement in variability of losses is between 32 and 42%. Finally, the reduction (improvement) in the divergence of actual core losses from the theoretical ones is between 30 and 38% for the small cores and 82 and 87% for the large cores.

3. Reduction of iron losses using neural networks

The first step in the application of artificial intelligence methods in transformer manufacturing is to collect measurements during the first stages of core construction. When a satisfactory number of measurements has been collected, these methods are applied in order to learn the information included in the databases. This training stage is executed offline providing an iron loss prediction model. The second stage of the method includes the on-line application of the iron loss prediction model in order to reduce iron losses of assembled transformers.

3.1. Iron loss prediction model

For the creation of the learning sets, the measurements collected during the initial stages of transformer manufacturing are grouped according to the supplier, grade and thickness of magnetic material. Each different supplier, grade and thickness of magnetic material is categorized as a different subset, called environment in the sequel. For example, the environment #1 is characterized by magnetic material of grade M3, thickness 0.23 mm, while the supplier of material was SUP_A (Supplier A).

Extensive experiments have shown, however, that the performance of the neural networks is unacceptable, if samples of all environments were used as training set. Almost similar results have been observed even if the parameters of the environment (i.e., the supplier, grade and thickness of the magnetic material) are used as neural network input vectors. Hence, the training set is divided into subsets each corresponding to a specific environment. This approach has provided very satisfactory results. For example, the environment #1 consists of 2240 actual industrial measurement sets (samples). 1680 of them are used as training data in the learning process of the neural network, while the rest (560) as test set (TS). As validation set, we have used the one-fourth of the samples of the learning set.

A multilayer feedforward neural network structure with one input layer, one hidden layer and a single output neuron was found to provide satisfactory results. The input neurons correspond to eight attributes selected by applying decision trees [6]. These attributes include the rated magnetic induction as well as the magnetic material average specific losses of the four individual cores at 15 000 and at 17 000 Gauss. Moreover, attributes such as the ratio of actual over theoretical total weight of the four individual cores and the ratio of actual over theoretical total iron losses of the four individual cores are also selected. The rest three attributes are formed by the combination of other measurements. The number of neurons of the hidden layer was selected so that the generalization performance of the network to be satisfactory for each given environment. For example, for the #1 environment, one hidden layer of five neurons was found completely adequate. The activation function for all neurons is the sigmoid function.

Figs. 1 and 2 present the quantile–quantile (Q–Q) plots of the specific iron losses, for the environment #1, using the typical loss curve [7] and the proposed neural network method, respectively. According to the Q–Q plot method the data of real specific iron losses are plotted versus the predicted ones. Perfect prediction lies on a line of 45° slope. It is observed that the neural network method provides more accurate results than the typical loss curve. This is due to the learning capabilities of the neural network approach as well as due to the fact that more parameters (attributes) are taken into consideration. In all the environments examined, the neural network method provides an improved accuracy by more than 45% in relation to the current practice (loss curve).

3.2. Transformer assembly

The current technique used (referred to as conventional grouping process) to reduce iron losses of assembled transformers is to pre-measure and assign a grade (quality category) to each individual core and then combine higher and lower graded individual cores to achieve an "average" value for the entire transformer.

In this paper, we enhance the conventional grouping process by proposing a new algorithm which exploits the

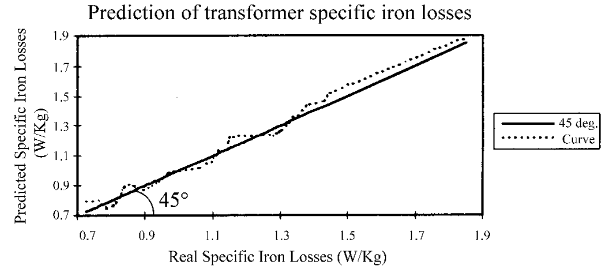

Fig. 1. Prediction of transformer specific iron losses, using the loss curve.

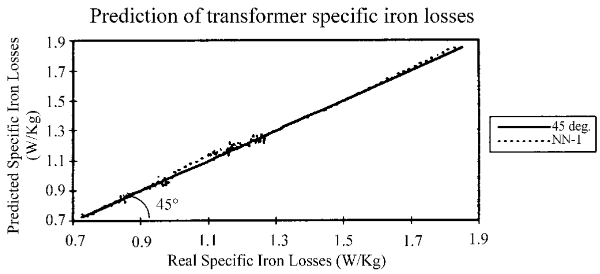

Fig. 2. Prediction of transformer specific iron losses, using the neural network method.

advantages of the neural networks. Assuming that, we have L small cores and L large cores, then $L/2$ transformers can be assembled. In this case, the algorithm comprises the following steps:

1. For each of the different combinations, calculate the neural network inputs (eight attributes) for each one of the $L/2$ transformers. Using the respective neural network weights and thresholds, calculate the network output (i.e., the specific iron losses of transformer) for each of the $L/2$ transformers and for all combinations.
2. For each of the different combinations and for each of the $L/2$ transformers, calculate the actual iron losses by multiplying the neural network output (specific iron losses) with the respective actual weight of transformer.
3. From all combinations, select the one providing the minimum absolute relative error in relation to the guaranteed to the customer iron losses. However, in case that the number of combinations is too large, only a randomly selected small subset of them is used to find a relative minimum value.
4. For the combination selected in 3, check if there are any transformers, which are not acceptable according to transformer acceptability criterion considered. If it occurs, then the respective cores should not be grouped, waiting (if possible) other cores of better quality and of the same production batch.

The proposed approach has been tested in different production batches during transformer construction, providing accurate results. In particular, the proposed neural network based grouping process provides an average absolute relative error (AARE) in the prediction of iron losses, smaller than 1.60% for all the production batches. This is compared with an AARE of 3.15% in prediction of transformer iron losses, usually observed by the current (conventional) grouping process.

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