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APPLICATION OF GENETIC ALGORITHMS TO CORE LOSS COEFFICIENT EXTRACTION

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Abstract—Core loss data are usually provided in the form of tables or curves of total loss versus flux density or frequency for electrical machine designers. These tables or curves can be used to extract the loss coefficients of the core loss formulas because accurate calculations of the coefficients have an important issue in electrical machine design. In this study, using original loss data given for M19 steel material, the core loss coefficients are calculated by the genetic algorithm developed in Matlab environment and electromagnetic analysis software (Ansoft Maxwell) is also used to extract the core loss coefficients in order to verify the proposed method. It is found that the exponent of flux density (B) depends on the flux range or the frequency range and these changes in the exponent of B can be correlated to the physical phenomenon of domain wall movement in response to an external field. As a difference from existing studies in literature, this study suggests a new method for extracting the core loss coefficients without any requirement for mathematical operations due to the nature of genetic algorithms and over the range of frequencies between 50–400 Hz and flux densities from 0 to 1.5 T, the new method yields lower errors for the specific core losses than those obtained by the magnetic field analysis software.

1. INTRODUCTION

Calculation of loss coefficients of core materials plays an important role for the design of electric machinery. Manufacturers of core materials provide tables or curves of total loss versus flux density or frequency instead of giving core loss coefficients. Loss coefficients of a material can be extracted with the help of these tables or curves. There are some

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numerical approaches used for this process. However, there are always deviations between the original loss value and the calculated loss value due to the lack of the numerical approaches and the formulas. Hence, numerical approaches and equations, which represent the relationship between the total loss versus the flux density or frequency, need to be modified.

Recently, some outstanding algorithms have been presented in literature. Some of these methods include genetic algorithm, simulated annealing, particle swarm optimization, ant colony optimization and evolutionary algorithms [1]. These methods generate new points in the search space by applying operators to current points and statistically moving toward more optimal places in the search space. They rely on an intelligent search of a large but finite solution space using statistical methods. In addition, the algorithms do not require taking objective function derivatives and can thus deal with discrete variables and non-continuous objective functions [2].

Genetic algorithm (GA) starts with an initial random population containing a number of chromosomes which represent a probable solution to the problem. The fitness of each chromosome in the population is calculated using a "fitness function" that evaluates how well each particular member solves the given problem [3].

In this study, loss coefficients of a material called M19 steel are determined by using both genetic algorithms and magnetic field analysis software (Ansoft Maxwell). The total core losses of this material are calculated using these determined coefficients for both methods. The obtained results are compared to the given original loss data specified by the manufacturer. Since the comparisons show the results of the proposed method are closer to the original loss data, the feasibility of genetic algorithms is verified successfully.

2. CORE LOSSES IN ELECTRICAL MACHINERY

Core loss in a magnetic material occurs when the material is subjected to a time varying magnetic flux [4]. In electric machinery, energy is dissipated in the windings, core and surrounding structures. Core losses under sinusoidal flux condition have been divided up in three components: hysteresis loss P_h, eddy current loss P_c and excessive loss (or anomalous) P_e [5]. When the external field is reduced or reversed from a given value, domain wall motion again occurs to realize the necessary alignment of domains with the new value of the magnetic field. The energy associated with domain wall motion is irreversible and manifests itself as heat within the magnetic material. This loss is known as hysteresis losses [6]. For a given material, the loss is proportional to the frequency and is a function of the peak flux density to which it is subjected. The metallurgical structure of the magnetic material, including its electrical conductivity, also has a profound effect upon the magnitude of the loss.

As the magnetic field reverses direction and cuts across the core structure, it induces a voltage in the core known as 'eddy' voltages. This action in turn causes eddy currents to circulate in the core. Also, the lines of flux that link the copper conductor windings of the transformer pass through the core itself and contribute to induce the electrical currents in it. These eddy currents heat up the core and dissipate power [7]. Eddy current losses can be reduced by making the core of a stack of sheets electrically insulated from each other. Silica is used as insulating material between the sheets. The eddy current paths are reduced in the core made of insulated sheets and thus the eddy current losses are minimized [7–9].

The origin of the excess loss can be well understood by describing the magnetization dynamics in terms of a random distribution of magnetic correlation regions (i.e., groups of interacting domain walls), termed magnetic objects (MO). It assumes that the excess loss is governed by the statistical distribution of the local threshold fields at which different MOs become magnetically active [6].

2.1. Computation of Core Losses

According to the Steinmetz equation, measurement and calculation of core losses are normally made with sinusoidal flux density of varying magnitude and frequency [10]. The specific core losses p_v in watts per pound (or watts per kilogram) can be expressed by

$$p_v = p_h + p_c + p_e \tag{1}$$

where the eddy-current loss is

$$p_c = k_c \left(f B_m\right)^2 \tag{2}$$

the hysteresis loss is

$$p_h = k_h f B_m^2 \tag{3}$$

and the last term corresponds to the excess or anomalous loss component. Despite the complicated physical background and based on a statistical study, Bertotti has proposed the simple expression for the excess losses, similar to that of the eddy-current losses, but with an exponent value of 1.5 [11].

$$p_e = k_e \left(f B_m\right)^{1.5} \tag{4}$$

where f is the frequency of the external magnetic field, B_m is the flux density, k_h, k_c and k_e are the coefficients.

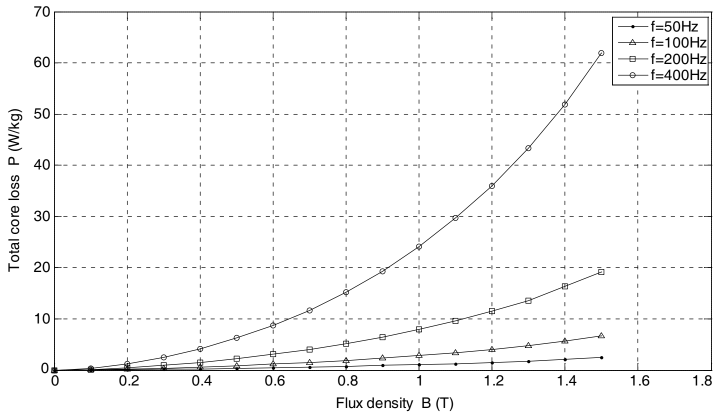

Figure 1. The measured manufacturer's data.

The eddy-current loss, which is often referred as "classical loss", can be estimated with a constant value coefficient calculated as

$$k_c = \pi^2 \sigma \frac{d^2}{6} \tag{5}$$

where σ is the electrical conductivity and d is the lamination thickness. Analytical estimations or typical values are not available for k_h and k_e. Thus, the total core loss can be expressed as

$$p_v = k_h f B_m^2 + k_c \left(f B_m\right)^2 + k_e \left(f B_m\right)^{1.5} \tag{6}$$

Manufacturers often use multiple sets of Steinmetz coefficients to represent the core loss of their materials, each set being "tuned" to more accurately reflect core loss over a particular range [10]. The measured manufacturer's loss data for M19 steel are shown in Figure 1.

Core loss measurements are provided over a range of frequencies from 50 to 400 Hz and in flux density increments of 0.1 T [12].

3. GENETIC ALGORITHMS

The genetic algorithms (GAs) are optimization techniques that have been used to solve general problems with objective functions that do not possess continuity and differentiability properties. Because of GAs' robustness and their uniform approach to large number of different classes of problems, they have been used in many applications [13, 14]. A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes or minimizes the "fitness" function [2].

The operation of the GA changes slightly depending on the base of the numbers to apply the genetic operator such as crossover, mutation, mating and elitism. The selection process evaluates each chromosome by some fitness mechanisms and assigns it a fitness value [15]. Although there are many techniques for the selection of parents, the tournament selection procedure is used in this study because it is computationally more efficient and more amenable to parallel implementation [16]. According to this selection scheme, two small groups of chromosomes are randomly selected from the mating pool and each group usually consists of two or three chromosomes. The chromosome with the highest fitness in each group becomes a parent. Enough of these tournaments are held to generate the required number of parents [1].

At the end of each selection process, crossover and mutation operations are performed, respectively. Crossover operation can be considered as a form of local search in the search space, whereas mutation operation induces random variations in the population, thus keeps the algorithms exploring diverse areas [2].

3.1. Chromosome Structure

Genetic algorithms begin by defining a chromosome or an array of variable values to be optimized and each variable in a chromosome is called a 'gene' [1]. Hence, core loss coefficients should be coded to a chromosome. In classical genetic algorithms, binary numbers are mainly used. However, in this paper, real number coding method is chosen in order not to consider how many bits are necessary to accurately represent a coefficient and also to reduce the processing time. Each variable can take any value from 0–20.

While Eq. (6) provides useful insights into the loss mechanism, it has been shown that this equation does not accurately reflect the core loss data provided by a steel manufacturer. To reduce these errors between the original loss data curve and the estimation curve, a new modification using the genetic algorithm can be represented by

$$p_v = \underbrace{k_h f}_{K_1} B_m^x + k_c \left(f B_m\right)^2 + \underbrace{k_e f^{1.5}}_{K_2} B_m^{1.5} \tag{7}$$

where K_1, K_2 are the coefficients and x is the exponent of hysteresis loss, which are variable with frequency f and flux density B. It can be noticed that the exponent, x, should be optimized as well as K_1 and K_2. Eq. (7) is found in good agreement with the original core loss data if the parameters are properly selected. The core loss coefficients

k_h and k_e in Eq. (7) can be obtained by

$$k_h = \frac{K_1}{f} \tag{8}$$

$$k_e = \frac{K_2}{f^{1.5}} \tag{9}$$

In this study, each gene can take any value in the range 0–20. Since there are three parameters to be optimized, the structure of a chromosome can be represented in Figure 2.

$$[K_1, \quad x, \quad K_2] \equiv [0 \ldots 20,\ 0 \ldots 20,\ 0 \ldots 20]$$

Figure 2. Chromosome structure.

3.2. Defining Evaluation Criteria

The fitness of each chromosome in the population is calculated using a "fitness function" that characterizes how well each particular member solves the given problem [17]. In the actual problem, the aim is to reduce the deviations between the original loss data and the resulting curve based on Eq. (7) parameters of which are optimized by the GA. Let i denote the i-th point of the data on the measured loss characteristic curve.

$$F = \sum_i \left[P_{vi} - \left(K_1 B_{mi}^x + k_c f^2 B_{mi}^2 + K_2 B_{mi}^{1.5}\right)\right]^2 \tag{10}$$

where F is the sum of squared errors (SSE) and P_{vi} is the i-th data on the original loss curve. The fitness of each chromosome in the population is calculated according to this performance index represented in Eq. (10).

3.3. Design of the Genetic Algorithm

In this study, the population is composed of 8 chromosomes. Each chromosome represents three parameters to be optimized, which are coded in the range 0–20. The initial population is randomly created and is sorted from the fittest chromosome to the worst chromosome. Deciding how many chromosomes to keep is somewhat arbitrary. Using the discard rate of 50% results in discarding the bottom four chromosomes. The four with the highest fitness survive to the next generation and become potential parents to generate child population. Tournament selection process is applied among the potential parents and produces four offspring to replace the discarded chromosomes in the population. The crossover and mutation operations are also performed at the end of the natural selection process. In addition, elitism is used in this study, which means that the fittest individual of the population is transferred to the next generation without any change. That is, the fittest chromosome in the current generation is saved [17]. These steps continue until the termination condition is satisfied, except the creation of the initial population.

The detailed flowchart of the genetic algorithm is shown in Figure 3.

The aim of all these operations in this flowchart is to operate on the basis of the survival of the fittest and hence to select the most appropriate chromosome in the search space.

4. SIMULATION RESULTS

In practice, the lamination steel manufacturers do not present the loss coefficients. They only provide the loss curves and tables in watts per kilogram (W/kg) or watts per pound (W/lb) versus flux density or frequency to indicate the combination of hysteresis loss, eddy current loss and excess loss for the design of electrical machines [6]. The classical estimation of core loss is systematically lower than the measured values. This underestimation of core loss is due to the waveform distortion, to the complexity of the electrical machine structures and to the complex behavior of dynamic hysteresis loops. For the analysis and calculation of core loss, the definition of the loss coefficients based on the original loss data or curves provided by the lamination steel manufacturers is essential [18].

In this paper, the core loss coefficients are extracted based on the original loss data supplied by a steel manufacturer using the formula represented in Eq. (7). In this formula, the coefficients K_1, K_2 and x are optimized to generate more proper shape to the Total Loss versus Flux Density or Frequency Curve. Under the same conditions, magnetic field analysis software (Ansoft Maxwell) is also utilized. The sum of the squared errors between the original loss data and the estimated loss data is calculated in the range of frequencies between 50 Hz and 400 Hz and is compared. The agreement between the experimental loss data and calculations based on Eq. (7) whose parameters are optimized by GA is more acceptable in the suggested method. Table 1 shows the parameters used in genetic algorithm.

In Figure 4, the hysteresis component of the total loss is a function of frequency to the first power, but the relationship between hysteresis loss and flux density varies depending on flux density or frequency.

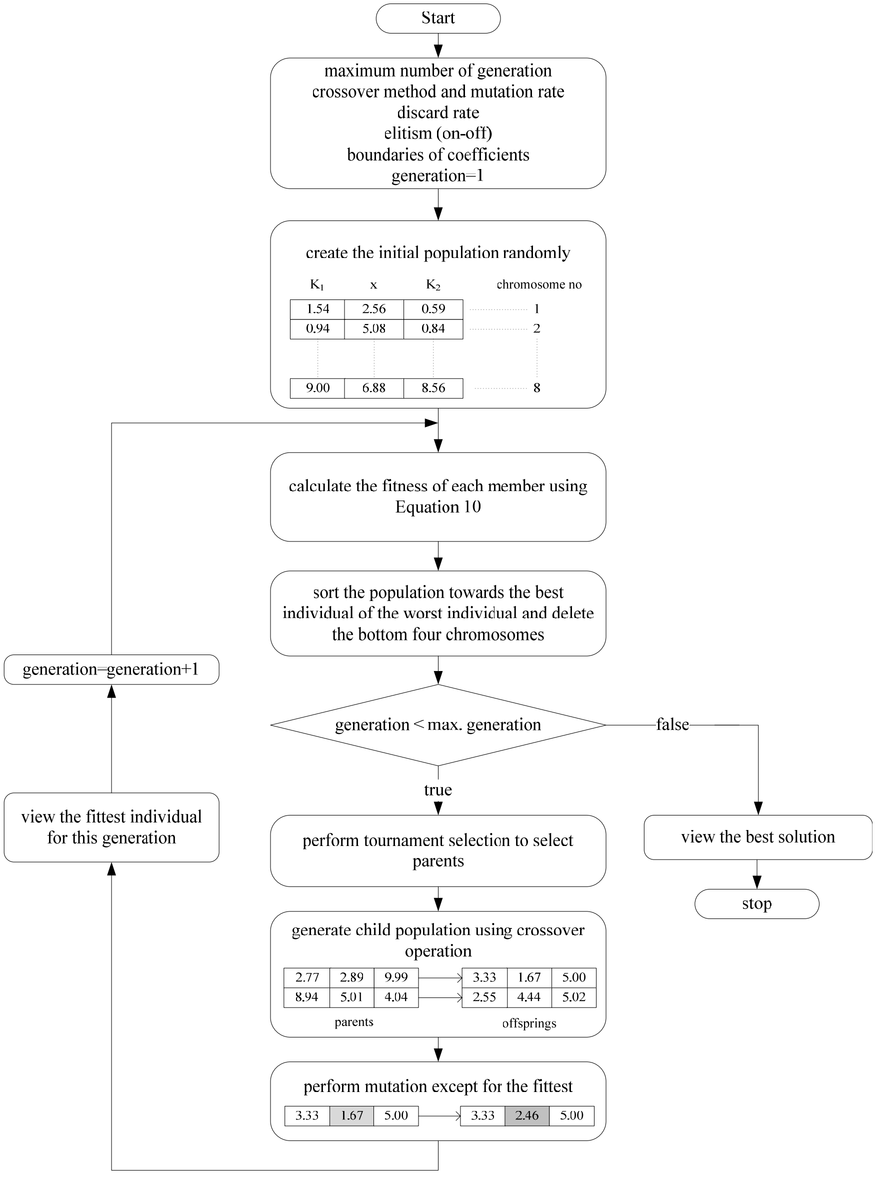

Figure 3. Detailed flowchart of the genetic algorithm.

The comparisons between the original core loss curves and the resulting curves obtained from magnetic analysis software are also given in Figure 5.

Table 1. The genetic algorithm parameters.

GA parameters	Values/Methods
Population size (N)	8
Maximum generation	500
Selection method	Tournament selection
Crossover type	Heuristic
Mutation rate (p_m)	0.60
Discard rate (p_d)	0.50
Elitism	On
Fitness function (F)	Eq. (10)

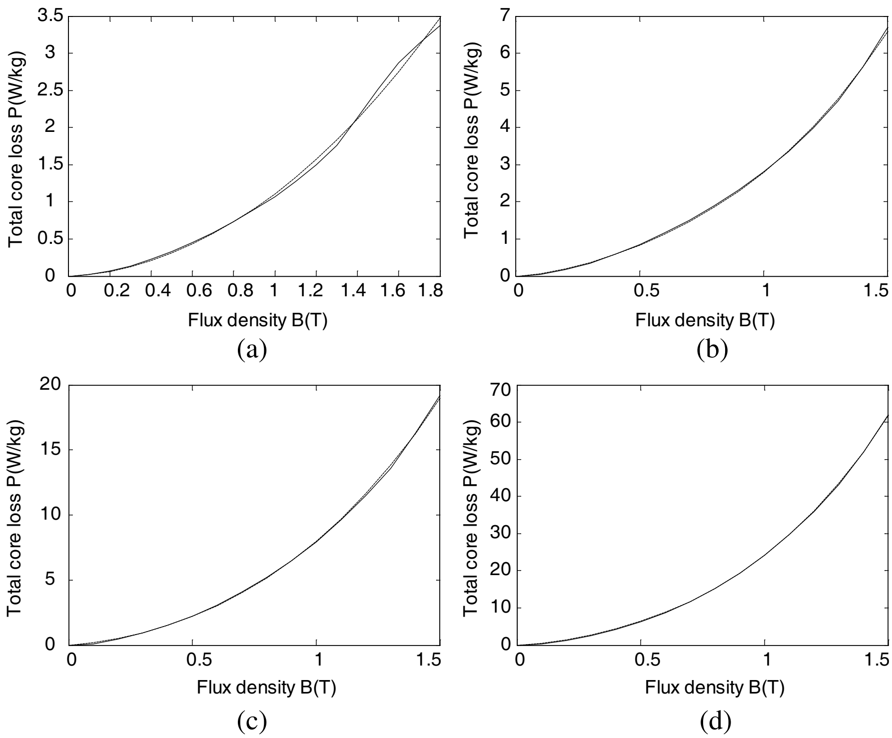

Figure 4. Comparisons between the manufacturer-provided loss curves (solid lines) and the calculations based on Eq. (7) (dashed lines) for M19 steel material at (a) $f = 50\,\text{Hz}$, (b) $f = 100\,\text{Hz}$, (c) $f = 200\,\text{Hz}$, (d) $f = 400\,\text{Hz}$.

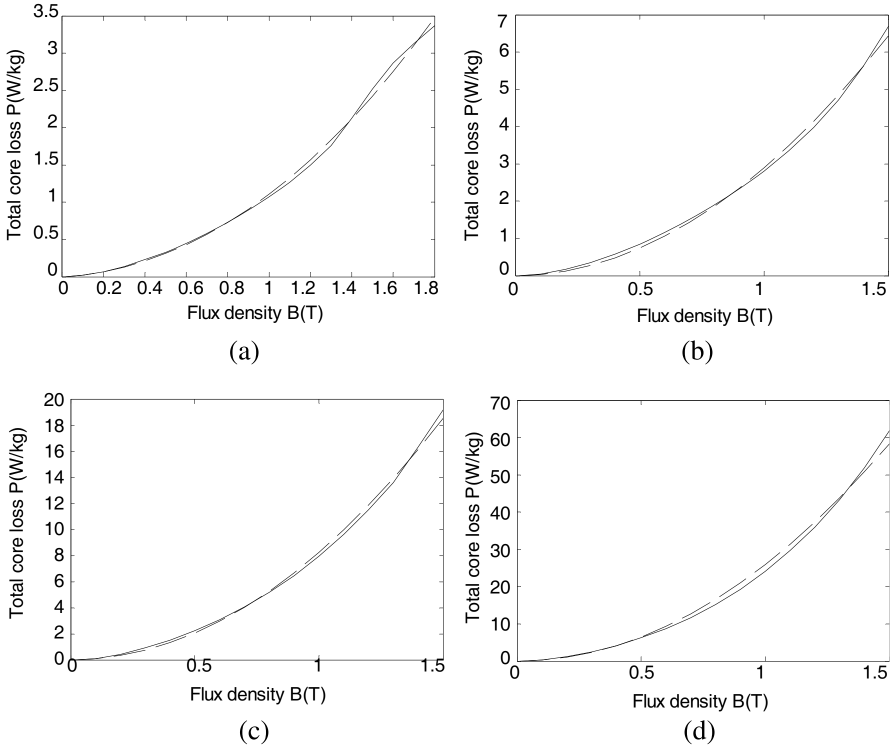

Figure 5. Comparisons between the manufacturer-provided loss curves (solid lines) and the resulting curves obtained from magnetic analysis software based on Eq. (6) (dashed lines) for M19 steel material at (a) $f = 50\,\mathrm{Hz}$, (b) $f = 100\,\mathrm{Hz}$, (c) $f = 200\,\mathrm{Hz}$, (d) $f = 400\,\mathrm{Hz}$.

It can be seen from Figures 4–5 that the formula defined in Eq. (7) fits better with the experimental data than the model defined in Eq. (6). Under low flux densities and low frequencies, this equation is in a good agreement with the original data. However, significant discrepancies between the calculation results of this model and the experimental data occur under high flux densities and high frequencies [6].

The training curves of the genetic algorithm according to the generation are shown in Figure 6. These training curves show the convergence of the GA along 500 generations.

In Figure 6, only very small improvements are noticed after 250 iterations. After an initial sharp drop, the best solution of the population remains relatively constant. It can also be seen that

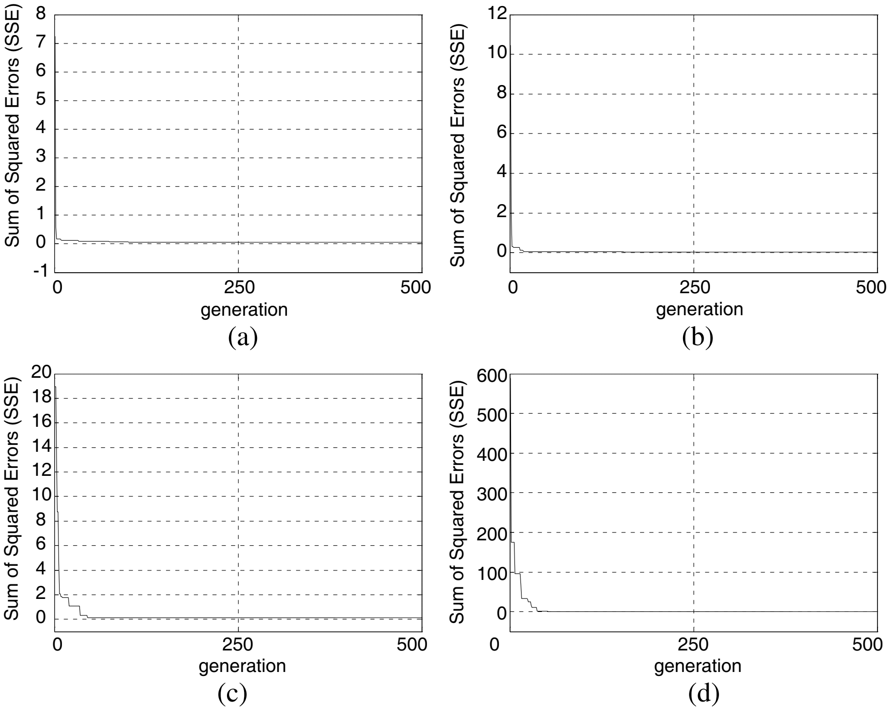

Figure 6. Convergence of the GA for (a) $f = 50\,\mathrm{Hz}$, (b) $f = 100\,\mathrm{Hz}$, (c) $f = 200\,\mathrm{Hz}$, (d) $f = 400\,\mathrm{Hz}$.

the best curves either stay the same or go lower than the previous generation due to elitism.

Reinitializing the random-number generator and running the algorithms again will produce different results. Changing the GA parameters, such as population size and mutation rate, will also produce different results [1].

According to four different frequency values, core loss coefficients and the calculated sum of the squared errors obtained from both the proposed method and the magnetic field analysis software (Ansoft Maxwell) are given in Table 2.

In Table 2, the core loss parameter units are in W/kg. It is easily seen that there are major differences between the proposed method and cad-based software according to the SSE values. For example, at 200 Hz, in genetic based parameter extraction, the performance index SSE is 0.1439 while it is about 1.09 in cad-based software. Similar results can be observed in other three frequencies. In both

Table 2. Comparison between the proposed method and cad-based software.

Frequency Values (Hz)	Genetic based parameter extraction				Cad-based parameter extraction		
	k_h	x	k_e	SSE	k_h	k_e	SSE
f=50	0.009512	2.3684	0.001675	0.0524	0.018174	0.000423	0.0548
f=100	0.004817	3.8209	0.002149	0.0279	0.025282	0.000169	0.1827
f=200	0.011230	3.1840	0.001795	0.1439	0.037302	0	1.0900
f=400	0.018057	3.4759	0.001782	0.3398	0.057145	0	28.322

extraction methods, the constant eddy loss coefficient is calculated from Eq. (5) and found $k_c = 1.6449.10^{-5}$. Finally, the match between the calculation of Eq. (7) and the original loss data is quite closer than that obtained by the magnetic field analysis software based on Eq. (6). It should be mentioned that in Eq. (7) the eddy current coefficient k_c is constant, whereas the hysteresis loss coefficient k_h, the excess loss coefficient k_e and the exponent of the flux density x are variables with frequency and the changes of the hysteresis loss coefficients k_h and x with frequency indicate the hysteresis loop area change, which reveals in turn the change of the material domain wall motion.

5. CONCLUSION

In this study, the core loss coefficients of M19 steel material are optimized using genetic algorithm developed in Matlab environment and electromagnetic analysis software in order to reflect the original loss data more accurately. As a difference from existing studies in literature, this study suggests a new method for extracting the core loss coefficients without any requirement for mathematical operations due to the nature of genetic algorithms. These coefficients are determined by both the proposed genetic-based approach and the traditional approach. The observations show that the proposed method has a better performance for estimating the original core loss data. As a result, the extracting method of the loss coefficients and the agreement between the original loss data and the calculation of Eq. (7) are more acceptable and effective.

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