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Abstract — **An efficient method, which is called the "inverse distribution function method", for calculating the magnetic field strength H from the flux density B through the Preisach model is developed. By using the method, H can be directly obtained without iteration from B which is calculated by the usual FEM, with the magnetic vector potential as unknown variable. The effects of the dimension n of inverse distribution function on the CPU time and the memory requirements are investigated through a numerical example by increasing the dimension n of the inverse distribution function. It is shown that the additional CPU time for taking account of hysteresis is negligible when n is less than about 200.**

Index terms — **Hysteresis, Preisach model, finite element method**

I. INTRODUCTION

Problems in the finite element analysis using the Preisach model [1], which is one of the modeling methods of hysteresis properties of magnetic materials, are investigated. The classical Preisach model is not suitable for B-oriented method, because the additional iteration is required to find H from the calculated B. Because, the distribution function is defined with H. Moreover, it may require huge memory for storing hysteretic magnetization processes at respective positions in magnetic materials.

In this paper, the inverse distribution function is introduced for the practical analysis using Preisach model. By using this method, H can be directly calculated without iterations. A technique for reducing the memory requirements is also discussed. The effects of the dimension n of inverse distribution function on the CPU time and the memory requirements are examined.

II. SCALAR PREISACH MODEL

In a scalar Preisach model [2], it is assumed that the magnetic material consists of many elementary interacting particles and each of them can be represented by a rectangular elementary hysteresis loop having positive or negative magnetized state as shown in Fig.1. By increasing H, the elementary particles of which the switching field Hu is lower or equal to H turn to up-magnetized state of magnetization $+Ms$. With the decreasing H, the particles of which the magnetization is positive remain in their position until H is decreased to the switching field Hl. At $H \leq Hl$, the particles reverse from one stable magnetization position to the other one providing magnetization of $-Ms$. The change of magnetization of magnetic material can be represented as the reversal of domains. If the number of particles, having switching fields (Hu, He), is $\kappa(Hu, Hl)$, the magnetization of particles having (Hu, Hl) is equal to $+Ms\cdot\kappa(Hu, Hl)$ or $-Ms\cdot\kappa(Hu, Hl)$.

According to the Preisach model, the magnetization M can be determined as the magnetization assembly of particles having the distribution function $\kappa(Hu, Hl)$.

$$M = \int_{Hu}\int_{Hl} \alpha(Hu, Hl)\cdot Ms\cdot\kappa(Hu, Hl)\mathrm{d}Hu\mathrm{d}Hl \quad (1)$$

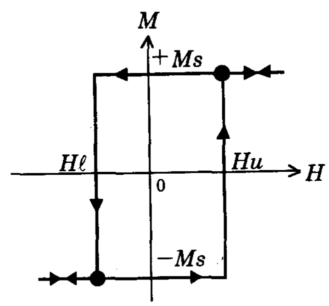

Fig.1. Elementary hysteresis loop.

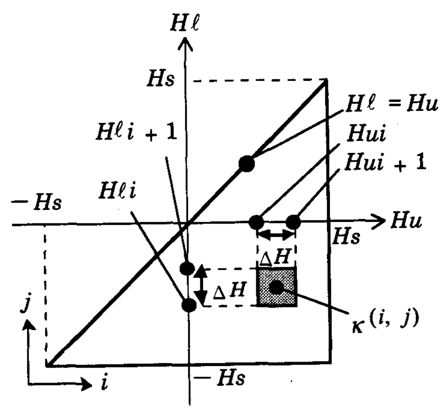

Fig.2. Preisach triangle.

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The definition region of switching fields (Hu, Hl), the Preisach triangle, is shown in Fig.2. The number of particles $\kappa(Hu, Hl)$ which are defined in the Preisach triangle is called as a distribution function. As Ms can be arbitrarily determined, it is set at unity for all elementary particles. $\alpha(Hu, Hl)$ is the elementary hysteresis operator and has values of +1/2 and -1/2 corresponding to up and down positions of the elementary hysteresis loop.

The distribution function can be obtained by using the transition curves shown in Fig.3. Applying finite change in the descending field, it results finite change in the magnetization. If the magnetic field strength between $-Hs$ and Hs is discretized to n parts having the interval ΔH, it results n cells in both directions. Fig.4 shows an example of n=4. When the applied magnetic field strength H is decreased from H_2 to H_3 along the curve ①, the integration K of the following equation along the curve ① corresponds to a_2 in Fig.4 (a)

$$K = \int_{Hu} \int_{Hl} \kappa(Hu, Hl) \mathrm{d}Hu \mathrm{d}Hl \qquad (2)$$

The integration K along the curve ② in the range of $H_3 \leqq H \leqq H_2$ is equal to b_1 in Fig.4 (b). Then, K(4,3), which is defined in the region of $H_2 \leq Hu \leq H_1$, $H_3 \leq H \leq H_2$ in Fig.4 (b), is obtained as (a_2-b_1).

By using the above-mentioned $K(i, j)$, (1) can be rewritten as

$$M = \sum_{i}^{n} \sum_{j}^{n} \alpha(i, j) \cdot Ms \cdot K(i, j) \qquad (3)$$

III. Inverse Distribution Function Method

The distribution function with H as variables is not suitable for the analysis of hysteresis properties by using the usual B-oriented finite element method of which the unknown variable is the magnetic vector potential, because the distribution function is a function of H. Therefore, many iterations are necessary to obtain H from the calculated B.

The inverse distribution function method for obtaining H directly from B is conceived to avoid such iterations. In this method, the inverse transition curves shown in Fig.5 is utilized to obtain the inverse distribution function. The inverse distribution function can be obtained in the similar way as the case of the distribution function. Fig.6 shows an example of cells of n=4. The integration $K'(4,3)$ of the inverse distribution function at i=4 and j=3 is obtained as (a_2-

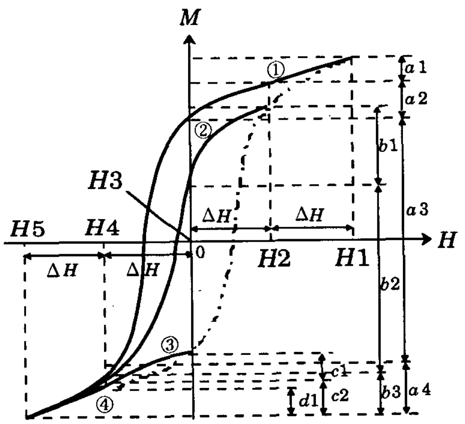
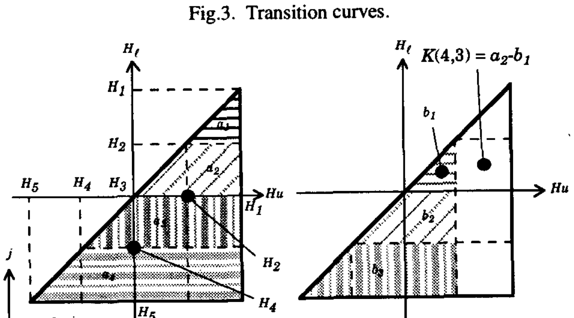


Fig.3. Transition curves.



(a) transition curve ① (b) transition curve ②

Fig. 4. Relationship between transition curves and distributiuon function.

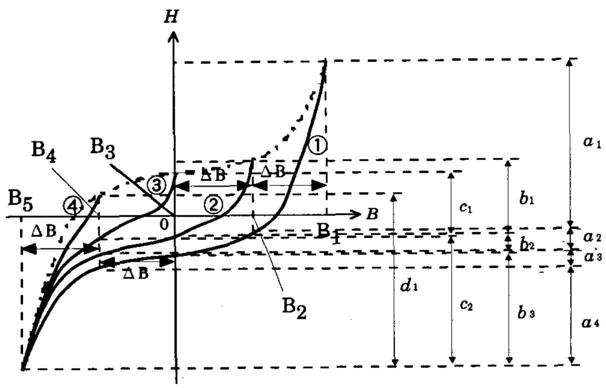
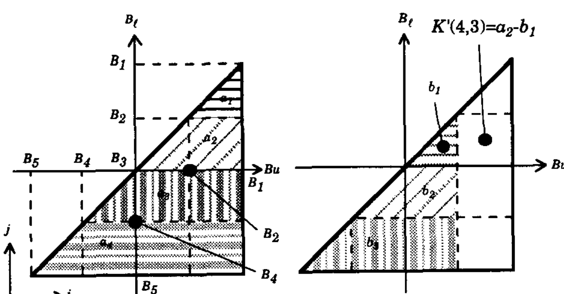


Fig.5. Inverse transition curves.



(a) inverse transition curve ① (b) inverse transition curve ②

Fig. 6. Relationship between inverse transition curves and distributiuon function.

b_l) as shown in Fig.6.

The magnetization history is stored in $\alpha(Hu, Hl)$. In this case, huge memory ($=n^2/2$) is required in storing +1/2 and -1/2 regions in the Preizach triangle. Alternately, the magnetization history can be stored by memorizing the position of the border line between +1/2 and -1/2 regions [4].

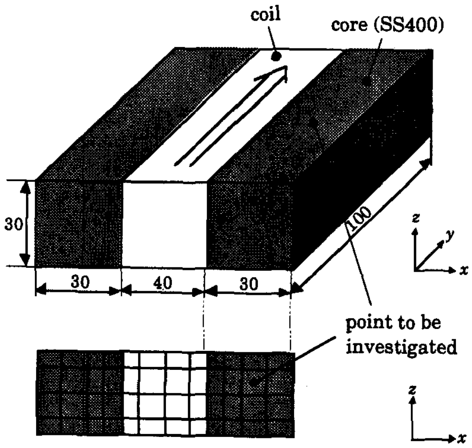
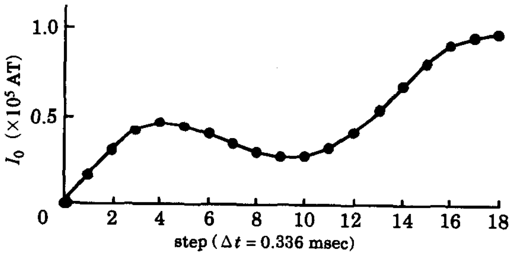


Fig.7. Simple model for calculating H.



$I_0(t) = 1.0 \times 10^5 \times \{0.75 \times \sin(100\pi t) + 0.25\sin(400\pi t)\}$

Fig. 8. Waveform of magnetizing current.

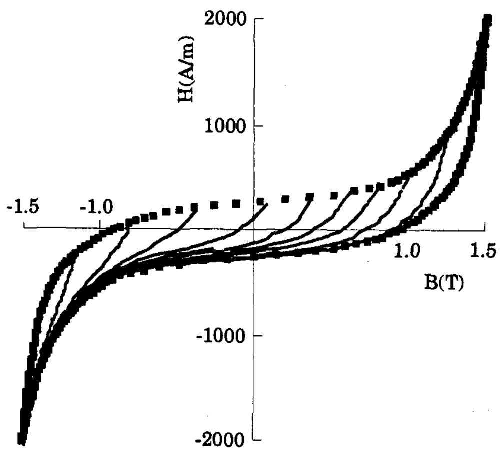


Fig.9. Measured inverse transition curves(SS400).

This reduces the memory requirement from $n^2/2$ to only n.

The newly conceived inverse distribution function method is applied to a simple model as shown in Fig.7, and compared with the ordinary distribution function method and the neural network(NN) method [5]. A coil with the current shown in Fig.8 is located between two cores made of steel(SS400). The eddy current is ignored. Fig.9 shows the inverse transition curves of steel measured by using a very low frequency excitation system to avoid the eddy current effect. Fig.10 shows the obtained inverse distribution function. Fig.11 shows the calculated magnetization process. Table I shows the

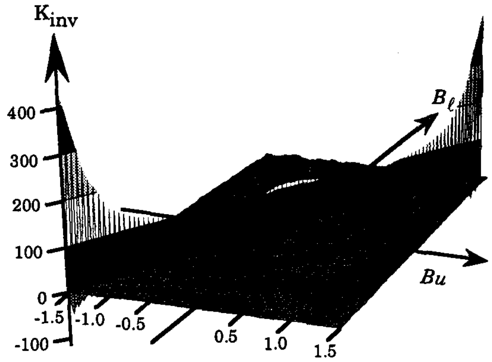


Fig.10. Inverse distribution function.

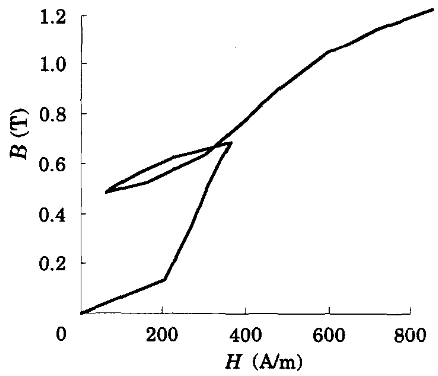


Fig.11. Simulated magnetization process.

TABLE I
Memory requirements and CPU time

method	memory (MB)	CPU (s)
distribution function	70.1	62,569
neural network	8.8	2,806#
inverse distribution function	10.0	2,579

Computer used: HP735 (45 MFLOPS)
dimension n: 200
CPU time for training of NN: 32,800 (s)

comparison of memory requirement and CPU time. The number n of cells (dimension) of the Preisach triangle is chosen as 200. The table denotes that the memory requirements for the neural network method and the inverse distribution function method are considerably reduced compared with the distribution function method. As the neural network method needs a long CPU time for the training of the network, it can be concluded that the inverse distribution function method is preferable from the viewpoint of memory requirement and CPU time.

IV. Examination On Memory Requirment And CPU Time

The effect of the dimension n of inverse distribution function on the memory requirements and CPU time is investigated using the model shown in Fig.12. The current waveform is denoted in Fig.8. The eddy current is ignored. The analyzed region is subdivided into 4,710 1st order brick nodal elements.

Fig.13 shows the effect of dimension n on memory requirements and CPU time. The CPU time increases nearly quadratically with n. The figure denotes that the CPU time for calculating hysteresis loop is negligible, if n is nearly equal to 200.

V. Conclusions

The obtained results can be summarized as follows:

(1) Three kinds of methods for calculating H from B through the Preisach model are discussed. It is shown that the newly conceived "inverse distribution function method" is better than other methods.

(2) The effect of the dimension n of inverse distribution function on the memory requirement and the CPU time is investigated. It is illustrated that the CPU time for calculating hysteresis loop is negligible, if n is nearly equal to 200.

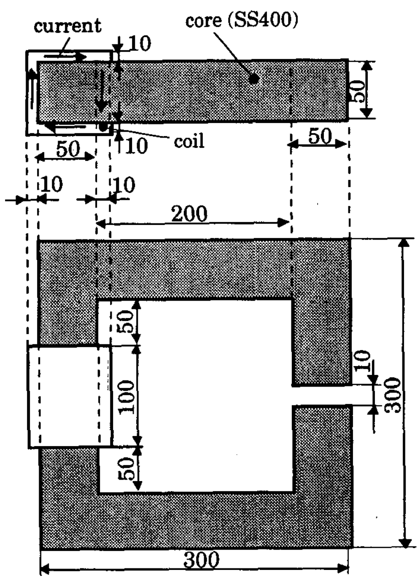
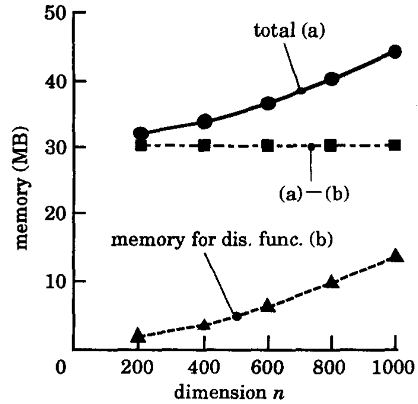
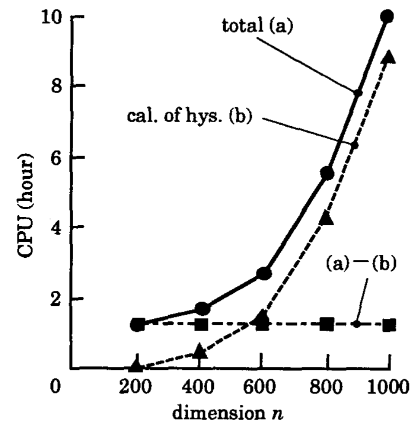


Fig. 12. Analyzed model.



(a) memory requirements



(b) CPU time

Fig. 13. Effect of dimension n on memory requirements and CPU time.

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