Applying Expert Systems and Fuzzy Logic for Core selection for High Frequency Power Transformers

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ABSTRACT - A large number of factors go into core selection in the design of high frequency power transformers. An experto - fuzzy system called CoGSA (Core Geometry Selection Aid) has been developed to aid the magnetic designer in selection of a core geometry. The system is based on Expert System and Fuzzy Logic techniques. The various decision components (Power, Cost, Shielding, Heating, Power Density etc.) are taken into account in the form of IF-THEN statements. The fuzzy logic is applied to take into consideration the uncertainty involved with the various factors.

1.0 INTRODUCTION

In the field of high frequency magnetics, the heuristics developed over a number of years play a large part in the design process. The techniques of expert systems and fuzzy logic form a powerful combination for modeling the heuristic based decision processes. An expert system captures the intuitive model of the problem in the form of IF-THEN statements which can be processed in two ways - Forward Chaining and Backward Chaining. The application of fuzzy logic captures the different shades of decision making thereby helping to model the problem realistically.

TRANSEX - an expert system for designing high frequency power transformer implements a form of decision making by evaluating an objective function [1]. This method of decision making has been replaced by implementing a process which employs a combination of expert system and fuzzy logic techniques. A separate module to assist TRANSEX users called - CoGSA (Core Geometry Selection Aid) has been developed for this very purpose. It gathers various inputs from the user and then processes these inputs by expert system and fuzzy logic techniques. It displays the decision process by quantifying the final output and displaying in a graphical form.

2.0 EXPERT SYSTEMS

Expert system is a branch of Artificial Intelligence (AI). This field of AI attempts to discover methodologies which could lead to higher intelligence levels in machines. The underlying principle of embedding intelligence into machines has been to achieve mechanized reasoning through symbols, non-algorithmic methods and concepts rather than numbers. TRANSEX [1] is an application of this technique.

3.0 FUZZY LOGIC

Fuzzy logic provides means of modeling the decision making process based on natural language words. The inexactness and the ambiguity of such words as low, high, tall, hot etc. can be incorporated into the decision making process without any compromise. The basic steps in the application of Fuzzy Logic are described below.

3.1 Fuzzy Sets: An element belonging to a fuzzy set can be defined by a function (called membership function) which can attain any value between 0 and 1. This is shown as follows:

\[ M_x : X \rightarrow [0,1] \] (1)

\( M_x \), the membership function, maps elements of \( X \) to a value between 0 and 1.

\[ M_x(x) = 1, \text{ means } x \text{ is totally in } X. \] (2)

\[ M_x(x) = 0, \text{ means } x \text{ is totally out of } X. \] (3)

\[ 0 < M_x(x) < 1, \text{ means } x \text{ is partially in } X. \] (4)

An output power of 200 W may be designated as high with full confidence ("certainly" high) or with half confidence ("somewhat" high) or very low confidence ("not" high). These confidence factors are designated as the degree of membership function. These values, as the name suggests are provided by the membership function which defines "high".

3.2 Fuzzification: For each of the crisp system inputs, a membership function is defined which helps transform these inputs into fuzzy inputs. For example, power of 1000 W can be transformed into "high" with 0.9 (on a scale of 0 to 1) degree of the membership function.

3.3 Fuzzy Inference: The fuzzy rules have 'IF-THEN' structure. These rules are evaluated on the basis of the fuzzy mathematics and the degree of membership is determined for the various outputs.

3.3.1 Fuzzy Mathematics: In this section, we present two fuzzy operators - 'AND' and 'OR'. Their operation is demonstrated by the examples shown below:

\[ \text{IF } x \text{ (degree of membership } = 0.2) \text{ AND } y \text{ (degree of membership } = 0.9) \text{ THEN } z \text{ (degree of membership } = 0.2) \]
IF x (degree of membership = 0.2) OR y (degree of membership = 0.9) THEN z (degree of membership = 0.9)

Thus as shown by the rules above, degree of membership for z is the minimum of that of x and y in the presence of the 'AND' operator and maximum of that of x and y in the presence of the 'OR' operator. This is shown below:

\[ M_{x\cup} = \text{MAX} (M_x, M_y) \]  (5)
\[ M_{x\cap} = \text{MIN} (M_x, M_y) \]  (6)
\[ M_{\overline{NOT}} = 1 - M_x \]  (7)

A number of rules may refer to the same output, and therefore may generate different degrees of membership. Under such circumstances, the output is awarded the maximum of all the generated degrees of membership.

3.4 Defuzzification: This process generates the membership functions for the outputs and obtains one crisp value for the output. One of the techniques of doing so is called Center of Gravity (COG).

3.4.1 Center of Gravity technique for defuzzification: Each membership function for the output is clamped to the maximum degree of membership obtained by that output. Such clamping action is called lambda-cut (alpha-cut). Further to this a single crisp point is found for the output by evaluating the following expression:

\[ \text{COG} = \frac{\int M_x \cdot x \cdot dx}{\int M_x \cdot dx} \]  (8)

The above formula in discrete form is shown below:

\[ \text{COG} = \frac{\sum M_x \cdot x}{\sum M_x} \]  (9)

4.0 CORE GEOMETRY SELECTION AID (CoGSA)

CoGSA has been developed in an expert system shell LEVEL5 Object 3.0 and Microsoft Excel. CoGSA helps a high frequency transformer designer select a core geometry and a particular core within that core geometry in the design of high frequency power transformers. CoGSA has two modules - the first module treats the individual core geometries and the second module treats the individual cores in the core geometries. The first step towards building such a system is the identification of the crisp inputs, construction of the user interface and establishment of the appropriate datastructures.

4.1 Crisp Inputs: The following quantities are provided to the first module as the crisp inputs: Power, Frequency, Heat Dissipation, Current, Voltage, Bobbin Cost, Winding Cost and Core Cost. The following quantities are provided to the second module as the crisp inputs: Flux Density, Frequency, Duty Cycle, Current Density.
calculated when the pushbutton 'evaluate' is triggered. Figure 2 and 3 belong to the second module. It is an independent module which on the basis of throughput power and temperature rise decides the optimum core size. Figure 2 shows the display which accepts such inputs as flux density, frequency, duty cycle, efficiency and output power. These inputs are transmitted to a computational intensive database developed in Microsoft Excel through the DDE protocol. These inputs are used to calculate throughput power and temperature rise of all the cores in the database. These two parameters - temperature rise and throughput power are then processed using fuzzy inference to quantify each of the core sizes for their degree of optimality (adequacy or COG). Figure 2 displays the throughput power for the various core sizes within a particular core geometry. Figure 3 shows the quantification of the degree of optimality (adequacy or COG) for the various core sizes within a particular core geometry.

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4.2.2 Datastructures for the crisp inputs: An object - 'crisp input' is defined which has the following attributes - power, frequency, voltage, current, core cost, winding cost, bobbin cost, EM/RFI shielding and heat dissipation. These attributes are used to store the user inputs.

4.2.3 Generalized Datastructure for each of the Crisp Inputs: This generalized datastructure has the following attributes - very low, low, medium, high, very high. These attributes are used to store the degree of membership for the various parameters for the specific user input.

4.2.4 Datastructure for storing lambda cuts: The values of the lambda cuts for the various core geometries are stored in the datastructure called - lambda cuts. It has the following attributes - one, two, three, four and five. As there are five membership functions over the complete universe of discourse (all possible values for a crisp input), therefore there are five lambda cuts which are stored in the attributes of the class - lambda cuts.

4.2 Datastructures (Objects): The various datastructures have been defined in CoGSA. The expert system shell LEVEL5 Object 3.0 allows for easy organization of the data in terms of logic by allowing one to define objects. These objects, when defined properly can lead to a very short concept to implementation time. Some of the objects or datastructures are explained below:

4.2.1 Datastructures for each of the Core Geometries: These datastructures have a generalized class structure with the following attributes: very poor, poor, fair, good, very good, final value, evaluate. The attributes - very poor, poor, fair, good and very good store the values for the degree of membership for these parameters. The attribute - final value stores the value calculated using the COG defuzzification technique. The attribute - evaluate is used as a simple switch to trigger the process of calculating the final value for that particular core geometry.

4.3 Membership Function: Figure 4 shows the membership functions. These functions have been defined over a normalized universe of discourse (The x-axis values). This function has been used for all the crisp inputs in both the modules. The whole normalized range has been divided into five membership functions - very low, low, medium, high and very high.

4.4 Forward Chaining on the Crisp Inputs: For each of the core geometries, a generalized set of forward chaining rules are formulated. These rules are triggered on the command of the user [1]. A complete set of rules for a core geometry are derived from the following geometry specific table:
TABLE I
CHARACTERISTICS OF POT CORE GEOMETRY

<table>
<thead>
<tr>
<th>Use of the Pot Core IS</th>
<th>Very Poor</th>
<th>Poor</th>
<th>Fair</th>
<th>Good</th>
<th>Very Good</th>
</tr>
</thead>
<tbody>
<tr>
<td>When...</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Core Cost IS</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bobbin Cost IS</td>
<td>Very High</td>
<td>High</td>
<td>Medium</td>
<td>Low</td>
<td></td>
</tr>
<tr>
<td>Power IS</td>
<td>Very High</td>
<td>High</td>
<td>Medium</td>
<td>Low</td>
<td>Very Low</td>
</tr>
<tr>
<td>Freq. IS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shield. IS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heat Dissipation IS</td>
<td>Very High</td>
<td>High</td>
<td>Medium</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Voltage IS</td>
<td>Very High</td>
<td>High</td>
<td>Medium</td>
<td>Low</td>
<td>Very Low</td>
</tr>
<tr>
<td>Curr. IS</td>
<td>Very High</td>
<td>High</td>
<td>Medium</td>
<td>Low</td>
<td>Very Low</td>
</tr>
</tbody>
</table>

The above table is for the pot core geometry. The top row in the bold letters indicate the use of pot core under the given condition(s). For example, generally most of the pot cores have high core cost compared to other core geometries. This fact is reflected under the column 'Core Cost IS'. Related information can be derived from this fact. Therefore, for 'medium core cost, the use of pot core is fair'. This is done to refine the decision making process. It also eliminates the possibility of a specific core geometry not being considered because of the combination of certain specific inputs. Similar tables have been constructed for the other core geometries as well. The tables essentially tend to capture the realistic model of the decision making process. By applying Fuzzy logic such a model can be transformed into a computer based model.

Once the process of providing input is complete, the user can initiate the forward chaining process. In the first module, the forward chaining rules and the fuzzy inferencing go hand in hand. The modification of the forward chaining rules to accommodate the fuzzy inferencing is as shown below:

IF heat dissipation requirement is high
THEN M(very good OF EE core) = MAX( M( heat dissipation), M(very good OF EE Core))

The degree of membership for the output 'very good OF EE core' is always decided by the maximum of the previous value and the current value. Therefore, an output can have a number of rules and its degree of membership is decided by the rule which applies the best (in other words which maximizes the value of the degree of membership). The main advantage of such a technique is that a great degree of modularization is possible in formulating the rules. Therefore, Table I can be divided into 29 forward chaining rules. The advantage of such an approach is the ability to refine the decision process easily. The disadvantage is the problem of managing such a large number of rules.

For the second module the following table shows the model for selecting an appropriate core size:

TABLE II
RULES RELATING TEMP. RISE AND POWER TO A CORE'S UTILITY

<table>
<thead>
<tr>
<th>Power Difference</th>
<th>very low</th>
<th>low</th>
<th>medium</th>
<th>high</th>
<th>very high</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temp. Rise</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>very low</td>
<td>very good</td>
<td>good</td>
<td>fair</td>
<td>poor</td>
<td>very poor</td>
</tr>
<tr>
<td>low</td>
<td>good</td>
<td>good</td>
<td>fair</td>
<td>poor</td>
<td>very poor</td>
</tr>
<tr>
<td>medium</td>
<td>fair</td>
<td>fair</td>
<td>fair</td>
<td>poor</td>
<td>very poor</td>
</tr>
<tr>
<td>high</td>
<td>poor</td>
<td>poor</td>
<td>poor</td>
<td>poor</td>
<td>very poor</td>
</tr>
<tr>
<td>very high</td>
<td>very poor</td>
<td>very poor</td>
<td>very poor</td>
<td>very poor</td>
<td>very poor</td>
</tr>
</tbody>
</table>

For the given inputs - flux density, duty cycle, efficiency, output power and frequency, the two parameters can be decided for each of the core sizes - output power and temperature rise. Given these two parameters a fuzzy rule can be formulated as follows:

IF temp rise is very low AND power difference is very low
THEN the use of the core size is very good

The power difference is the difference between the throughput power of the core and the required output power. Similar rules can be formulated for other conditions as well. These rules go through the fuzzy inferencing. A crisp output, which indicates the degree of optimality, is obtained for each of the core sizes.

5.0 RESULTS

Consider Table III. Column nos. 2 and 3 display the COG values (the degree of optimality) for the various core geometries for input conditions A and B. Conditions A and B are as shown below:

<table>
<thead>
<tr>
<th>Power Difference</th>
<th>COG</th>
</tr>
</thead>
<tbody>
<tr>
<td>very low</td>
<td></td>
</tr>
<tr>
<td>low</td>
<td></td>
</tr>
<tr>
<td>medium</td>
<td></td>
</tr>
<tr>
<td>high</td>
<td></td>
</tr>
<tr>
<td>very high</td>
<td></td>
</tr>
</tbody>
</table>
Core Geometry EE EC ETD

Input Condition A: (Power = 20 W, Frequency = 20 kHz, Power Loss = 0.2W, Current = 1A, Voltage = 20V, EMI/RFI Shielding Required).

Input Condition B: (Power = 100 W, Frequency = 200 kHz, Power Loss = 1W, Current = 2A, Voltage = 50V, EMI/RFI Shielding required)

From table III it can be seen that and Pot, RM and EP are best suited for Input Condition A and PQ and RM cores are best suited for Input Condition B. Corresponding to input condition A and B, following are the inputs to the second module respectively,

A: (Bmax = 1000G, Duty = 0.95, Efficiency = 0.99, Power = 20W, Frequency = 20 kHz, Current Density = 450 A/cm2).

B: (Bmax = 800G, Duty = 0.95, Efficiency = 0.99, Power = 100W, Frequency = 200 kHz, Current Density = 450 A/cm2).

Corresponding to condition A, it can be seen in the figures 5, 6, 7 and 8 that for each of the core geometries a distinct maxima can be obtained in the form of its calculated COG value reflecting the degree of optimality. For example, the maximum COG value among EE cores is approximately 0.72 for 2 stacked cores of 813E343 (See Fig. 5). Similarly, among the pot cores, the maximum COG value is obtained by the core 2213 (See Fig. 6). Among RM cores, the maximum COG value is obtained by RM8 core (See Fig. 7). For the given condition, a complete spectrum of cores along with their throughput power and the COG value are shown in Fig. 8. Corresponding to condition B, it can be seen in figure...
9 that for each of the core geometries a distinct maxima exists. This maxima indicates the optimum size of the core. The final value of the degree of optimality can be obtained by combining the outputs of the two modules. For example, for input condition A, RM core geometry has the COG value of 0.75 from module 1 and RM8 has the COG value of 0.76 from module 2. Combining the two, by fuzzy mathematics the final COG value is 0.75 (minimum of the two values). Similarly, a final COG value can be obtained for all the cores in that database. For condition B, the final degree of optimality for the RM8 core is 0.4.

6.0 DISCUSSION

It has been shown in this paper that by combining the expert system and fuzzy logic techniques, an optimum core geometry and an optimum core size within that geometry can be selected. The decision making process is non-numerical, non-algorithmic and heuristic in nature. The conventional programming techniques are unable to provide a realistic model of the dynamics of decision making. The methods implemented in CoGSA model the dynamics of core geometry selection in an efficient fashion.

REFERENCES