Artificial Intelligence-based Design Approach to Magnetics

Kapila M. Warnakulasuriya, Gayashan Porawagamage, David Hughes

***Abstract*— A large number of design parameters are taken into consideration in arriving at the optimum design of a magnetic component. Extensive studies carried out in the area of magnetic design optimization have shown that as many as forty parameters can govern the quality of a magnetic design. Most of these parameters can take over two hundred values each making countless possible design permutations for a particular application. A human designer can eliminate a large number of these permutations with expert knowledge experience, which is not necessarily the best converging approach to the most optimum design. This paper explains an artificial intelligence-based design approach that supersedes an experienced human designer.**

***Index Terms*— Magnetic Designs, Artificial Intelligence, Design Optimization, Parametric Designs.**

I. Introduction

THERE are many design parameters that are taken into consideration in arriving at the optimum design of a magnetic component. It is rarely the case that the values of all the parameters are known at the time of the start of the design. In most situations not even the suitable range of values for some of the governing parameters are known at the start of the design. In certain applications depending on the level of circuit simulations carried out by the application engineers, the ideal values for certain parameters are known and available for the magnetic designer.

On the other hand, in certain applications, the application engineers and the system designers would like to have practically achievable parameters of the magnetic components for them to use as an input for the electronics system design. This provides them the opportunity achieve a holistic optimization of the overall system. Below is a comprehensive list of design parameters that are usually taken into consideration in arriving at a magnetic design. This list is not exhaustive, However, it includes the parameters that affect most of the practical magnetic designs. Further it is also important to note that the significance of these parameters can change from application to application.

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TABLE I
DESIGN PARAMETERS

No	Parameter	unit
1	Primary voltage(s)	V
2	Secondary voltage(s)	V
3	Rated power (continuous)	W/VA
4	Operating frequency, f	Hz
5	Primary inductance, LP	mH
6	Secondary inductance LS	mH
7	Leakage inductance, LL	µH
8	Primary DC resistance Rp	Ω
9	Secondary DC resistance Rs	Ω
10	Primary AC resistance Rpac	Ω
11	Secondary AC resistance Rsac	Ω
12	Interwinding capacitance, CWW	nF
13	Turns ratio	
14	Primary current, Ip	A
15	Secondary current, Is	A
16	Volt-time product/Et constant	Vs
17	Isolation test voltage	kV
18	Total allowable load loss	W
19	Allowable no-load loss	W
20	Efficiency	
21	Primary overvoltage possibility	V
22	Details of voltage harmonics	V
23	Details of current harmonics	A
24	Static shield requirements	
25	Magnetic shield requirement	
26	Earthing requirements	
27	Creepage distance	mm
28	Clearance	mm
29	Distance through insulation	mm
30	Electrical tolerance percentage	
31	Dimensions (width, length and height)	mm
32	Weight,	kg
33	Ambient temperature	ºC
34	Allowable temperature rise	ºC
35	Cooling Method (e.g. natural convection, forced air, active water cooed, passive water-cooled, oil natural, forced oil, cold plate mounted etc)	
36	Insulation class (e.g. Class A, Class B, Class F, Class H etc.)	
37	Insulation type (dry type, oil etc)	
38	Noise level, (dB)	
39	Degree of protection (e.g. IP56)	
40	Pollution degree (I, II or II)	

In addition to the design optimization possibilities generated by a large number of permutations possible with the above parameters magnetics designers have a choice of number of constructions.

1. Toroidal core construction
2. Stadium core constructions

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3. EI core construction
4. UI core construction
5. 3UI core construction
6. Y core construction
7. Other non-standard core constructions

These different possible constructions provide further design optimisation possibilities.

The possible permutations that come out as a result of such a large number of parameters are in the range of ten to the power hundred and forty which is a number higher than the number of atoms on the Earth. The designer's expertise, experience and the magical nature of the human brain make it possible to narrow down these permutations for several hundred solutions in a relatively short time. However, this requires a high degree of subject expertise. Then the designer has to carry out several detailed calculations to select one or two permutations from that.

The possibility of doing that on a computer with a linear programming approach is practically impossible. Even with the modern powerful computers, it can take several hours or days to arrive at the design solution. After attempting statistical methods and expert learning approaches the authors decided to investigate this problem with artificial intelligence approaches.

Science the 21st century, computer AI technology and its related technology have received much attention and interest from many researchers. The theory based on the computer artificial intelligence technology has also made a major breakthrough, providing ideas for the design of the product. Computer AI technology has expanded the scope of involving and exploring products, and the scope of the application category of computer AI technology has also increased [1][2]

II. CONSIDERATIONS OF MAGNETIC DESIGNS

A. Transformer construction and cooling method

As an initial step of the transformer design process, a suitable construction for the transformer has to be decided. There are several existing transformer constructions such as toroidal core construction, stadium core constructions, EI core construction, UI core construction, 3UI core construction, Y core construction, and Other non-standard core constructions. An experienced human designer can narrow down these choices to one or two constructions almost instantly. However, the accuracy of the selection of final construction and the optimization highly depends on the designer's experience, and the comprehensiveness of the calculations and simulations carried out. Time taken to that can significantly.

The selection of the cooling method in most situations is not the magnetic designer's choice. However, there is a clear trend that nowadays the system designers and system architects get the magnetic designers involved at the initial stage of the final system design, especially in the case of high-power high-frequency power converter designs. There are many cooling methods available some of them are conventional and some of them are very modern. Below is a list of cooling techniques available for a magnetics

1. Natural convection
2. Forced air.
3. Active water-cooled.
4. Passive water-cooled.
5. Oil natural
6. Forced oil.
7. Cold plate mounted etc.
8. The use of heat-conducting channels.
9. Use of heat sink walls for thermal management

B. Transformer core selection and core loss estimation

The advantages and disadvantages that different core materials provide in a particular application are evaluated and thereby the magnetic designer arrives at the best magnetic solutions for the application.

A range of core materials is presented in the market including several grades of ferrite, such as 3C90, 3C93 and 3C97, three versions of nanocrystalline materials ANTAINAO, FINEMET, VAC, Amorphous materials and high silicon steel e.g. 6.5% Si JFE steel standard 3.0 % Si steel etc.

The most commonly used formula for the calculation of core material losses is the one given below which is known as the Steinmetz equation.

$$P_v(t) = kf^{\alpha}B^{\beta}$$

where B is the peak flux amplitude, P_V is the time average power losses per unit volume, f is the frequency of sinusoidal excitation and α and β are constants calculated based on curve fitting.

C. Conductor selection and winding losses estimations

The selection of optimum conductor type and arrangement are crucial in magnetic designs. Careful consideration of the skin effect and the proximity effect needs to be made to arrive at an optimal selection of the conductors in order to avoid the generation of excessive losses and thereby high temperature rises or even in certain cases thermal runway conditions [3,4]. The advantages and disadvantages of different conductor geometries and materials such as Copper and Aluminum are to be considered. Approaches must be taken to minimize the skin effect and the proximity effect. These include minimizing the number of winding layers and sandwiching windings carrying currents of opposite directions are explained which is also a significant analytical exercise.

D. Control of leakage inductance and Impedance

Accurate estimation of Impedance and leakage inductance of transformers is an important but challenging aspect of a magnetic design. Both these parameters depend on the physical construction and the geometry of the transformer. The accurate prediction of values becomes more and more difficult as the physical size of the transformer increases. This is due to the increased significance of the construction and the geometry of the product on these parameters. Further, the maneuvering of construction and geometry targeting specific values of impedance is difficult due to the lack of predictability [5]. Mathematical approaches are used to estimate the impedance and leakage inductance of magnetic components. The effects of the coil geometry, cooling channels, the transposition of the parallel wound conductors etc. are addressed in these mathematical approaches.

E. Thermal management of magnetic designs

One of the most important limiting factors for magnetic design is temperature rise induced by core losses and winding losses. The temperature rise is dependent on its surface area, cooling environment and power losses. To verify that temperature does not exceed material specification and can meet safety requirements, an estimation of the temperature rise is an important design consideration in the design process. Thus, magnetics designers use empirical and various thermal simulation techniques formulas for the estimation of temperature rise.

III. PARAMETRIC DESIGN APPROACH

Conventionally magnetic designers arrive at one or two design solutions for a particular application [6-8]. As opposed to this conventional design approach, the authors have also introduced a parametric design approach that provides a complete set of multiple solutions that are more accurate for a given application. The parametric design process is based on algorithmic thinking that enables the expression of parameters and rules that together, define, encode, and clarify the relationship between design intent and design output. This approach is commonly used in architectural applications and in some areas of design engineering [9][10]. The introduction of a parametric approach for the magnetic design is believed to be difficult due to the complexity of the problem. However, this has been made possible by the use of artificial intelligence algorithms discussed below.

IV. ARTIFICIAL INTELLIGENCE-BASED APPROACH

The authors have used an artificial-intelligence-based approach to face the challenges in magnetics design and to arrive at an optimized solution in a very short time duration compared to a human designer. This also provides a complete set of parametric solutions of magnetics designs for a particular application. Once the system is mathematically modelled so that the algorithm can solve the problem efficiently, an appropriate optimization algorithm is executed with random initial points. This process continues until the system obtains a predetermined number of designs.

V. OVERCOMING THE CHALLENGES IN DESIGN

The authors present a mathematical model for a toroidal transformer and the concept can be extended to other configurations. This model consists of discrete and continuous decision variables used to mathematically define a transformer. Decision variables are selected in such a way as to try to limit the number of variables as much as possible. This is important because the calculation load increases exponentially as the number of variables increases

Some assumptions have been made to simplify the model, which is acceptable for practical implementation.

Assumptions

1) The insulation thickness of one specific winding is the same across the entire length.

2) Windings are placed adjacent to each other or evenly spaced within a layer.

VI. MATHEMATICAL MODEL

The below sections defined the mathematical model of the system.

A. Evaluation of possible transformer constructions

Mathematical equations represent the relationship between the various parameters present in a transformer. A number of equality and inequality constraints are also defined when considering the practical aspect of design. The function of the algorithm is to satisfy all pre-defined limitations and to minimize or maximize the given objective function. There can be different objective functions such as weight, cost, and total loss of efficiency and the objective function may vary depending on the application used.

As Transformer modelling is well established in the field, the following sections describe only the mathematically challenging and modified specific models.

TABLE 2
UNITS FOR MODEL PARAMETERS

Symbol	Quantity	unit
M_i	Material decision variable	-
B	magnetic flux density	T
f	Frequency	Hz
K	Transformer constant	
L	length	m
n_i	No of the Inner layers without strands	
n_o	No of the outer layer without strands	
N_i	No of the inner layers with strands	
N_o	No of the outer layers with strands	
T_r	Temperature rise	^{0}C
C_{id}	Core – internal diameter	m
x_c	Core – cross-section length	m
t_{ic}	Core – thickness of the insulation layer	m
N_{st}	No of the strands per cable	
F_w	Final weight	kg
F_{id}	Final internal diameter	m
F_{od}	Final outside diameter	m
F_v	Final volume	m^3
L_{total}	Loss - total	W
h	Height - core	m
N_p	No of the primary turns	
N_s	No of the secondary turns	
R	Resistance	Ω

Evaluating each of the core materials one by one is challenging and computationally inefficient, given the large volume of materials on the market. Therefore, it is necessary to include all the materials in the mathematical model to solve the problem more efficiently. Therefore, the material is treated as a discrete decision variable and the relevant constrain is added to select only one material per design.

B. Estimation of core losses and evaluation of different magnetic materials

Decision variable

$M_i \in \{0, 1\} \quad \forall i \in N$

Flux density =

$$\sum_{i=1}^{n} M_i B_i$$

Loss per unit volume =

$$\sum_{i=1}^{n} M_i K_i f^{\alpha_i} B_i^{\beta_i}$$

Constrain for material selection

$$\sum_{i=1}^{n} M_i = 1$$

Transformer winding order calculation

C. Calculation of the length of the cable

The mathematical model is detailed for the toroidal type transformers and this concept can be extended to other configurations as well.

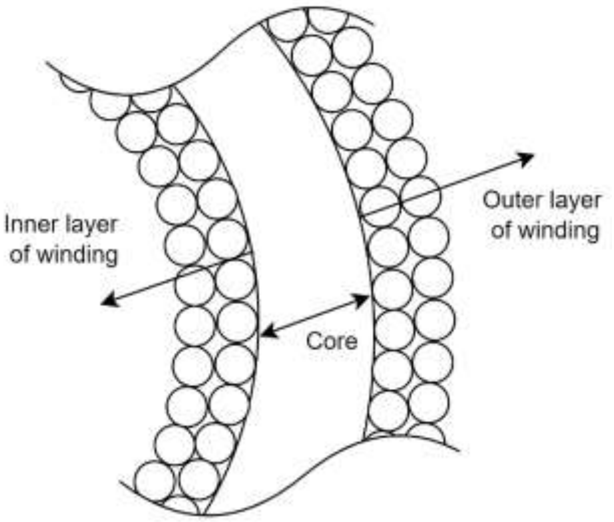

Fig. 1. Top view of the first two layers of a toroidal transformer.

Let's take a cross-section

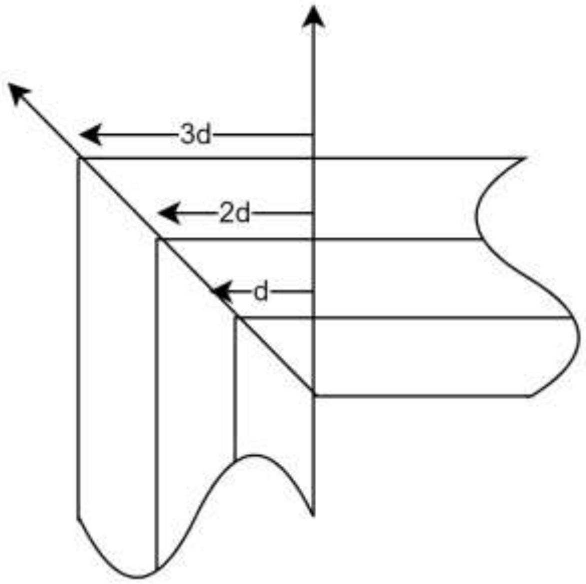

Fig. 1. Cross selection of the toroidal transformer core. The three winding layers are shown in the figure and the section where the length of each layer increases due to bending is calculated as a multiplication of cable diameter.

Direct increase in length

$$L_{direct} = 2N_{st}(X_c + 2t_{ic}) + 2N_{st}(h + 2t_{ic})$$

Increase length in outside winding

$$L_{out\ increase} = 4\pi(C_{id} + 2X_c + 2t_{ic} + (1.5)d) + \cdots. + 4\pi(n_o - 1)(C_{id} + 2X_c + 2t_{ic} + (n_o - 0.5)d) + \cdots.$$

Taking the equation to a general form

$$L_{out\ increase} = 4\pi\left((\mathrm{C_{id}} + 2\mathrm{X_c} + 2\mathrm{t_{ic}})\frac{n_o(n_o - 1)}{2} + 0.5\mathrm{d}\frac{n_0(2n_o + 1)(2n_o - 1)}{3} \right)$$

The length in inside winding can be derived from the same concept

$$L_{inner\ increase} = 4\pi\left((\mathrm{C_{id}} - 2\mathrm{t_{ic}})\frac{n_i(n_i - 1)}{2} + 0.5\mathrm{d}\frac{n_i(2n_i + 1)(2n_i - 1)}{3} \right)$$

Therefore, total length with strands is given below.

$$L_{with\ strands} = L_{direct} + L_{out\ increase} + L_{inner\ increase}$$

Calculation of total length of the cable

$$L_{with\ strands} = {L_{with\ strands}}/{stands}$$

Calculation of number of layers

$$N_i = n_i/N_{st}$$
$$N_o = n_o/N_{st}$$

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Constraints are listed below

$$N_{st} = \frac{\pi(\ N_o(2X_c +\ 2t_{ic} + C_{id}) + N_o^2(d + 2I_{con}))}{(d + 2I_{con})}$$

$$N_{st} = \frac{\pi(\ N_iC_{id} + N_i^2(d + 2I_{con}))}{(d + 2I_{con})}$$

D. Thermal model

Empirical equation has been used

$$T_r = \left(\frac{loss_{total}}{area_{total}}\right)^{0.812}$$

$$Loss_{total} = Loss_{cu} + Loss_{core}$$

$$Loss_{cu} = \sum_{i=1}^{n} I_i^2 R_i$$

$$area_{total} = \pi(C_{id} + 2X_c + 2t_{ic} + s)(h + 2t_{ic} + s) + 0.25\pi(C_{id} + 2X_c + 2t_{ic} + s)^2 - 0.25\pi(C_{id} - 2t_{ic} - s_1)^2 + \pi(C_{id} - 2t_{ic} - s1)(h + 2t_{ic} + s_1)$$

E. Parametric solution

Once all the parameters, equations, and limits have been defined, the model can be solved with an optimization algorithm to minimize a given objective function. The total weight of the transformer is taken as the objective function of the designs shown in the tables. The system evaluates the model with a minimum number of input parameters such as voltage and power as shown in Table 3.

TABLE 3
INPUTS TO RUN THE MODEL

Parameter	Value	Unit
Primary voltage	240	V
Secondary voltage	120	V
Secondary Power	1	kW
Frequency	50	Hz
Number of designs	1000	

Even though the model can run up to any number of designs, 15 number of designs are given in the tables. Calculated specification of the final transformer is detailed in Table 4 and calculated in core and winding parameters are listed in Table 5.

TABLE 4
MAIN SPECIFICATIONS OF THE DESIGNED TRANSFORMER

No	F_w (kg)	F_{id} (mm)	F_{od} (mm)	F_v (mm)	$Loss_{total}$ (W)	Tr (C)
1	4.79	40	99	740	53	60
2	4.79	40	99	740	53	60
3	4.79	40	100	753	53	60
4	4.80	45	103	754	54	60
5	4.81	50	108	781	56	60
6	4.82	55	111	781	57	60
7	4.82	55	111	781	57	60
8	4.83	38	99	750	53	60
9	4.83	40	100	753	53	60
10	4.83	45	104	767	54	60
11	4.83	50	107	763	56	60
12	4.85	37	98	744	53	60
13	4.86	45	103	763	55	60
14	4.86	45	104	782	55	60
15	4.86	45	104	782	55	60

TABLE 5
UNITS FOR MAGNETIC PROPERTIES

No	h (mm)	C_{id} (mm)	X_c (mm)	Np	Ns	d_p (mm)	d_s (mm)
1	57	78	22	572	300	1.6	1.7
2	57	78	22	572	300	1.6	1.7
3	56	78	22	574	302	1.6	1.5
4	55	82	21	595	313	1.6	1.7
5	53	86	21	621	327	1.6	1.4
6	51	90	21	642	339	1.5	1.7
7	51	90	21	642	339	1.5	1.7
8	57	77	21	566	297	1.6	1.7
9	57	78	21	572	300	1.6	1.7
10	55	82	21	595	313	1.6	1.7
11	53	86	21	611	321	1.2	2.2
12	58	76	22	555	291	1.2	2.3
13	55	82	21	587	309	1.2	2.2
14	55	82	21	590	310	1.0	2.2
15	55	82	21	590	310	1.0	2.2

VII. GAME CHANGING CONTRIBUTION TO THE INDUSTRY

Arriving at the most optimum solution for a magnetic design is generally a challenging task. It requires the evaluation of a large number of parameters. Experienced magnetic designers can arrive a solution over a reasonable amount of time. However, the designer has to limit the number of possible permutations during the evaluation process due the impracticality of evaluating the whole set of solutions. This narrowing down of options highly depends on the experience and the knowledge of the designer.

When the designer can use this approach as a tool for doing the design a large number of solutions can be generated

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within a few minutes of time. In a manual design optimization process even, an experienced designer would need an incomparably long time to arrive at that many designs which can practically be months of years of design time.

Further this approach would evaluate design parameter combinations that a human designer would not usually be able to look in to due to the time pressure.

Thus this approach will save the design time by over 95% when the designer uses this artificial intelligence based approach is used.

VIII. Conclusion

A human designer can eliminate a large number design parameter permutations with the expert knowledge experience they have. However, the design approach is not necessarily the best converging approach to arrive the most optimum design.

With the use of this artificial intelligence-based design approach a human designer can arrive a complete set optimized designs in a significantly shot period of time.

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