Optimum designing of a Transformer Considering Lay out Constraints by Penalty-Based Method using Hybrid Big Bang-Big Crunch Approach

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Abstract**—***Optimum designing of power electrical equipment and devices play a leading role in attaining optimal performance and price of equipments in electric power industry. Optimum transformer design considering multiple constraints is acquired using optimal determination of geometric parameters of transformer with respect to its magnetic and electric properties. As it is well known, every optimization problem requires an objective function to be minimized. In this paper optimum transformer design problem comprises minimization of transformers mean core mass and its windings by satisfying multiple constraints according to transformers ratings and international standards using a penalty-based method. Hybrid big bang-big crunch algorithm is applied to solve the optimization problem and results are compared to other methods. Proposed method has provided a reliable optimization solution and has guaranteed access to a global optimum. Simulation result indicates that using the proposed algorithm, transformer parameters such as core mass, efficiency and dimensions are remarkably improved. Moreover simulation time using this algorithm is quit less in comparison to other approaches.*

***Keywords—Transformer; Transformer design; Optimization; Hybrid big bang big crunch algorithm; Particle swarm optimization algorithm*.**

I. INTRODUCTION

Transformers are the most important appliance of the transmission lines and distribution networks. Traditionally, transformer industry has been using many approaches based on experience to design transformers aiming reducing of main and side costs. Transformer design must be satisfactory in the case of insulation capability and mechanical strength, furthermore windings must be robust against dynamic and thermal stress during short circuit faults. Transformer designing is a complicated problem due to the large number of parameters involved in design process with respect to designing constraints. The complexity of designing process revealed experience-based approaches deficiencies and this was the leading cause of consideration of other designing methods by engineers. As it is mentioned, designers had to rely on their experience and judgment to complete the designing process. Early research in transformer design attempted to reduce much of this judgment in favor of mathematical relationships [1,2]. Mathematical models were incorporated in design process using computers in order to defeat time consuming calculations related by reiterative design procedures [3]–[5]. Pioneers of transformer design who utilized computers for designing are [6, 7], which later [8] proposed an optimum method and updated the designing process. In this paper, designing of a transformer with ferrite core has investigated. There are other approaches that has utilized optimization-based methods to handle the selection of variables. In [9] a new method is proposed which begins with a guessed core geometry and then finds electrical and magnetic parameters values which using these parameters, the volt-ampere (VA) capacity of transformer is maximized and transformer loss is minimized. However, the method in [9] has not considered secondary constraints such as high efficiency, low winding regulation, and no-load current.An improved formulation and solution of the minimum loss problem [9] including high-frequency effects has presented in [10]. In this paper a set of instructions are given in order to choose a proper core but core dimensions were not taken as variables and therefore secondary constraints are ignored. Lagrange multipliers technique is used for finding minimum weight of an EI core transformer in [11]. It has assumed that most of the parameters of the transformer are fixed. In [12] an optimization procedure based on Monte Carlo simulation has presented. In this method lowest cost design is selected from an ample set of reasonable options created by random numbers. In recent years researchers have considered application of artificial intelligence approaches in transformer design: neural networks [13] were employed as a modeling strategy whereas genetic algorithm [14] was applied in the search process.

In this paper, optimum designing of a transformer is developed by using hybrid big bang-big crunch algorithm considering constraints by a new approach called penalty-based method. Optimum transformer design considering multiple constraints is obtained using optimal determination of geometric parameters of transformer with respect to its magnetic and electric properties. As it is well known, every optimization problem requires an objective function to be minimized. Hence in this paper optimum transformer design problem comprises minimization of transformers mean core mass and its windings by satisfying multiple constraints according to transformers ratings and prevalent international standards using a penalty-based method. Hybrid big bang-big crunch algorithm is applied to solve the optimization problem and results are compared to other methods.

The rest of the paper is organized as follows: in section two structure of particle swarm optimization (PSO) algorithm, big bang-big crunch (BB-BC) algorithm and hybrid big bang-big crunch algorithm (HBB-BC) in addition to penalty-based method are introduced. In section three objective function and transformer equations and constraints are presented. Simulation results and result analysis in addition to closing remarks of the paper are presented in section four and five, respectively.

II. INTRODUCTION TO PROPOSED ALGORITHM AND PENALTY-BASED METHOD

Considering the weakness of experience-based methods in transformer design which were not mostly time efficient and have included many errors, today intelligent and heuristic methods are employed for designing process.

A. Particle swarm optimization (PSO) algorithm

Particle swarm optimization (PSO) algorithm is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired from social behavior of birds and fishes [15]. PSO consists of a swarm of individuals named particles. Every particle is a representation of a candidate solution for optimization problem, specified by two vector: position and speed. Every particle finds its way toward the best found previous position ($X_i^{lbest\,(K,\,j)}$) and the best global position ($X_i^{gbest\,(K,\,j)}$). Related equations are updated as following:

$$V_i^{(K+1,j)} = W \times V_i^{(K,j)} + c_1 r_1\left(X_i^{lbest(K,j)} - X_i^{(K,j)}\right) + c_2 r_2\left(X_i^{gbest(K,j)} - X_i^{(K,j)}\right) \quad (1)$$

$$X_i^{(K+1,j)} = X_i^{(K,j)} + V_i^{(K+1,j)} \quad (2)$$

$$i = \{1,2,3,\dots,D\}, j = \{1,2,3,\dots,N\}$$

In this equations $V_i^{(K,j)}$ and $X_i^{(K,j)}$ are *i*th component of speed and position, respectively, corresponding to the *j*th particle produced in *k*th iteration. In addition *N* is number of population, *D* is total number of particle dimensions and *W* is inertia weight. Inertia weight controls the impact of the particles previous speed on its current value. Also *r1* and *r2* are random numbers generated constantly in interval [0, 1] and *c1* and *c2* are acceleration constant. A linearly reduced inert a weight from maximum value of W_{max} to minimum value of W_{min} is used for updating the inertia weight, as following:

$$W^K = W_{max} - \frac{(W_{max} - W_{min})K}{K_{max}} \quad (3)$$

whereK_{max} is maximum number and *K* is number of iterations. In this algorithm, maximum numbers of iteration is the criteria for cessation. This algorithm performs as follows:

- First step: setting initial value of problem and algorithms parameters
- Second step: generating primary population of N particle with stochastic positions in search space
- Third step: updating the position and performance of the mutation
- Fourth step: checking the cessation criteria

B. Big bang-big crunch algorithm

The big bang-big crunch (BB-BC) optimization algorithm is inspired by one of the theories of the evolution of universe, namely, the Big Bang-Big Crunch theory. The BB–BC optimization algorithm was introduced by Erol and Eksin in 2006 [16] which has low computational time and fast convergence.

This algorithm has two main steps: big bang phase and big crunch phase. In the first step, big bang phase, candidate solutions are randomly dispersed through the search space. Stochastic nature of big bang leads to energy dispersion or energy transmission from a regular form (converged solutions) to a chaotic form (a new set of solution candidates). Big crunch phase comes after big bang and inclines to get optimized. Big crunch is a convergence operator that has many inputs, however it has only one output, namely, center of mass. Here, the expression "mass" refers to fitness functions inverse. Center of mass is represented by $X_i^{C(K)}$, obtained using following equation [6]:

$$X_i^{C(K)} = \frac{\sum_{j=1}^{N} \frac{1}{f_j} X_i^{(K,j)}}{\sum_{j=1}^{N} \frac{1}{f_j}}, i = \{1,2,3,\dots,D\} \quad (4)$$

where $X_i^{C(K)}$ is the *i*th component of center of the mass in the *i*th iteration, $X_i^{(K,j)}$ is the *i*th component of the *j*th solution produced in the *k*th iteration, $f_j$is the value of the *j* th fitness function candidate, N is the population size in big bang phase and D is the number of control variables. After the big bang phase, algorithm creates new solutions using previous knowledge (center of mass) so as to utilize it for big bang purpose in the next iteration. This issue could be implemented by scattering new individuals around the center of mass using normal distribution performance in every direction. Standard deviation of this normal distribution function reduces with number of algorithms iterations increasing:

$$X_i^{(K+1,j)} = X_i^{C(K)} + \frac{r_j \alpha_1 (X_{imax} - X_{imin})}{K+1} \quad (5)$$

where $r_i$is a random number of a standard normal distribution that varies for every candidate, α_1 is a parameter for limiting size of search space, X_{imin} and X_{imax} are lower and upper range for ith control variable.

C. Hybrid big bang-big crunch algorithm

Hybrid big bang-big crunch (HBB-BC) algorithm is a multi-objective and stochastic search technique in which at every iteration several numbers of the search space is examined. In this paper, optimization capacities of PSO algorithm are used to improve the exploration ability of the BB-BC algorithm and avoid the trapping into the local optimum, Considering the incapability of BB-BC in finding the global optimum and with high likelihood gets trapped into the local optimum. One solution is to employ large number of candidates to avoid this problems, but this approach results in increasing the function evaluations and computational costs. This method utilizes the best position of every candidates $(X_i^{lbest(K,j)})$ and best global position $(X_i^{gbest(K,j)})$ for producing new solutions:

$$X_i^{(k+1,j)} = \alpha_2 X_i^{C(K)} + (1-\alpha_2)\left(\alpha_3 X_i^{gbest(K,j)} + (1-\alpha_3) X_i^{lbest(K,j)}\right) + \frac{r_j \alpha_1 (X_{imax} - X_{imin})}{K+1} \quad (6)$$

whereα_2 and α_3 are adjustable parameters that controls impact of global best and local best on the new position of the candidates, respectively. In order to access to a discrete position, new position is again defined using *Round(X)* function as given in (7) and new position is stated as $X_i^{\prime(K+1,j)}$:

$$X_i^{\prime(K+1,j)} = Round\left(X_i^{(K+1,j)}\right) \quad (7)$$

where*Round(X)* is a function which rounds the elements of X to the nearest integers. Using this position updating formula, particles are allowed to choose discrete values.Then the mutation operation is used to prevent the HB-BBC from trapping into the local optimum and to explore new search areas as follow:

$$X_i^{(K+1,j)} = round(X_{imin} + rand() \times (X_{imax} - X_{imin})) \quad (8)$$

where*rand()* is random number generated constantly in interval [0-1] and $Pm$is the likelihood of mutation. Process of the algorithm is as follows:

- First step: generating the initial candidate randomly and considering the constraints
- Second step: computing the fitness function for all of the solution candidates
- Third step: finding the center of mass
- Fourth step: computing the new candidate around the center of mass
- Fifth step: returning to the second step and repeating the process till cessation criteria is satisfied

D. Penalty-based method

Considering the constraints applied to the optimization problems, penalty-based method is appropriate approach for satisfying this limitations. This approach is viable in various ways such as cumulative, multiplicative and combinatorial approaches, which in this paper cumulative approach is used. In this approach after applying the constraints, objective function is updated as following:

$$f^{new} = f^{old} + \gamma(sum(ch)) \quad (9)$$

where$f$ is the objective function, *ch* is the sets of the constraints in the form of equality and inequality, *sum(ch)* is sum of the deviations of the constraints from the reference value and γ is the adjustment factor.

III. TRANSFORMERS EQUATION, CONSTRAINTS AND OBJECTIVE FUNCTION

A. Preliminaries

In this paper a single-phase dry shell-type transformer with ferrite core is considered. It is assumed that voltage and current has ideal sinusoidal waveforms. Figure 1(a) and 1(b) shows a front and top section view of a single-phase transformer, respectively. Based on this figure following equations are presented:

$$A_c = 2ct(m^2) \quad (10)$$

$$A_m = K_f A_c (m^2) \quad (11)$$

$$MLT = 4c + 2t + \pi b_w (m) \quad (12)$$

$$W_a = b_w h_w (m^2) \quad (13)$$

$$V_c = (2b_w + 2h_w + 4c) A_c (m^3) \quad (14)$$

$$V_w = MLT.W_a (m^3) \quad (15)$$

where in this equations A_C is cross section area of the center leg, A_m is the effective cross-sectional area of the center leg, *MLT* is the mean length of a turn, $W_a$is area of the windows of the both sides of the center leg,$V_C$is volume of the core, V_W is the volume of winding, t is depth of the core which is visible from above view of the figure, K_f is the core effective cross section factor and c, b_w and h_w are half of the width of the center leg, width and length of the windows of the both sides of the center leg, respectively, as shown in Fig. 1.

B. Mathematical model of objective function

The objective of optimization in this paper is minimizing the total mass of the transformer core and wiring material with respect to satisfaction of the limitations. The objective function is represented as follows:

$$f = m_c + m_{cu} = \rho_c K_f V_c + \rho_{cu} K_{cu} V_W \qquad (16)$$

where m_c is the total core mass, m_{cu} is wiring material mass, ρ_c is mass density of core, ρ_{cu} is mass density of wiring material, K_{cu} is copper fill factor of the wiring, V_C is volume of the core and V_W is the volume of winding. It is important to note that considering the price of one kilograms of every material (copper and other materials) used for manufacturing the core and windings, the objective function could be stated in the form of desired costs.

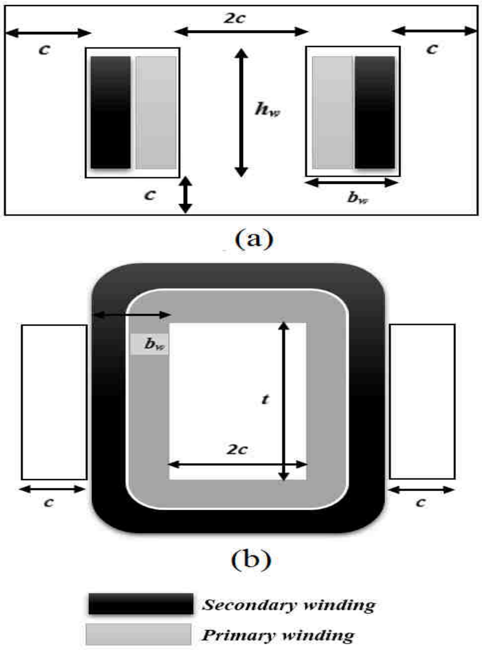


Fig. 1: (a) Front section view of single-phase transformer (b) Top section view of single-phase transformer

C. Mathematical model of transformer constraints

1) Induced voltage constraint in transformer

Assuming a sinusoidal waveform, effective value of the induced voltage at the primary side of the transformer is given as follows:

$$E_p = \sqrt{2}\pi f N_p B A_m = \sqrt{2}\pi f N_p B K_f A_c \qquad (17)$$

where E_p is the induced voltage at the primary side, f is the grid frequency, N_p is the wiring turns at primary side and B is the core flux density. Wiring turns of the secondary side is obtained using the following equation:

$$N_s = \frac{E_s}{E_p} N_p \qquad (18)$$

where N_s is the turns at secondary side and E_s is induced voltage at secondary side of the transformer.

2) Fill factor of the copper wiring constraint

Transformers optimum designing criteria is equality of copper loss is both primary and secondary sides. Mathematical statement of this criteria is given as followings:

$$\frac{A_{cu,s}}{A_{cu,p}} = \frac{N_p}{N_s} \qquad (19)$$

where $A_{cu,s}$ and $A_{cu,p}$ are secondary and primary conductor areas, respectively. This equation has two main points: first, primary and secondary copper wirings are distributed equally around the windows of the both sides of the center leg and second is equality of the area density of the primary and secondary conductors [17]. Fill factor of the copper wiring is given as following equation:

$$K_{cu} = \frac{N_p A_{cu,p} + N_s A_{cu,s}}{W_a} = \frac{2 N_p A_{cu,p}}{W_a} = \frac{2 N_p I_p}{W_a J} \qquad (20)$$

where I_P is the primary sides rated current and J is the area density of the primary and secondary conductors. Another important issue is the constraints on the layer thickness of the wirings. Assuming that the layer thickness of wirings at primary and secondary sides are equal:

$$\frac{N_{ls}}{N_{lp}} = \frac{N_s}{N_p} \qquad (21)$$

where N_{ls} and N_{lp} are numbers of turns per layer in the primary and secondary windings, respectively. In order to ensure that the transformer windings fit into the transformer window, the following additional requirement has to be met [17]:

$$d = \frac{A_{cu,s}}{f_l h_w / N_{ls}} = \frac{N_p I_p / N_s j}{f_l h_w / N_{ls}} \qquad (22)$$

where f_l is the gain factor for every layer.

3) Transformer thermal constraints

The thermal resistance regulation is necessary in optimal transformer design since it links the thermal performance to core and winding loss. In a dry-type transformer with natural air circulation, the dominant heat-transfer mechanism is by convection [18]:

$$R_\theta = \frac{1}{1.42 A_t} \sqrt[4]{\frac{h_w + 2c}{\Delta T}} \qquad (23)$$

where ΔT is rise in temperature, R_θ is thermal resistance and A_t is the transformer surface area given by (24) in whereas K_a is a constant parameter:

$$A_t = K_a \sqrt{2ctb_w h_w} \qquad (24)$$

Both the core loss and copper loss contribute to raising the transformer temperature. The core loss is given by (25)

$$P_c = \rho_c K_f K_c V_c B^\alpha f^\beta \quad (25)$$

where K_c , α and β are constant parameters which are suggested by manufacturers and designers. Whereas the copper loss, under the optimum design criterion embodied in (20), can be computed from following equation [2]:

$$P_{cu} = 2F_r \rho_w \frac{N_p MLT}{A_{cu,p}} I_p{}^2 = F_r \rho_w \left(2N_p A_{cu,p}\right) MLT J^2 = F_r \rho_w (K_{cu} W_a) MLT J^2 = F_r \rho_w K_{cu} V_w J^2 \quad (26)$$

where $\rho_w(\Omega.m)$ is the specific electrical resistance of the copper wirings, F_r is factor for considering the sin effect. The temperature rise constraint is therefore:

$$R_\theta (P_c + P_{cu}) = \frac{1}{1.42 A_t} \sqrt[4]{\frac{h_w + 2c}{\Delta T}} (P_c + P_{cu}) \leq \Delta T \quad (27)$$

4) Transformer efficiency constraint

The transformer efficiency is required to be greater than a pre-specified value named maximum efficiency(η_m) , therefore:

$$\frac{P_o + P_c + P_{cu}}{P_o} \geq \eta_m \quad (28)$$

where $P_o = S.P_f$ is the output power in watts. This equation can be rearranged into the following equation:

$$\frac{\eta_m}{1-\eta_m} P_c + \frac{\eta_m}{1-\eta_m} P_{cu} \leq P_o \quad (29)$$

5) Transformer no-load current constraint

Proper design of transformer requires limiting the transformer no-load current to a small fraction of the full load current. The no-load current can be found from the core loss component (I_C) and the magnetizing component (I_m) as following:

$$I_\varphi = \sqrt{I_m{}^2 + I_c{}^2} \quad (30)$$

The core loss component is:

$$I_c = \frac{P_c}{E_p} \quad (31)$$

The magnetizing component is given by Ampere law [19]:

$$I_m = \frac{B}{\mu} \frac{2b_w + 2h_w + 4c}{\sqrt{2} N_p} \quad (32)$$

where μ is magnetic permeability as $\mu = \mu_0 \mu_r$, whereas μ_0 is the permeability of free space and μ_r is relative permeability. The limit on the no-load current can be therefore expressed as

$$I_c{}^2 + I_m{}^2 \leq K_\varphi{}^2 I_p{}^2 \quad (33)$$

where K_φ is the ratio of maximum no-load current to rated current in primary side. Moreover core flux density restriction must be considered:

$$B \leq B_{sat} \quad (34)$$

where B_{sat} is the saturation flux density.

6) Transformer voltage regulation constraint

Both the transformer resistive resistance and magnetic resistance (leakage reactance) contribute to the transformer voltage drop. The resistive voltage drop can be computed from

$$V_R = 2F_r \rho_w \frac{N_p MLT}{A_{cu,p}} I_p.pf = 2F_r \rho_w N_p MLT.pf \quad (35)$$

where pf is the rated power factor. The reactive voltage drop referred to the primary side is given by

$$V_X = 2\pi f L_l I_p.rf \quad (36)$$

where rf is the reactive power factor and can be computed as following:

$$rf = \sqrt{1 - pf^2} \quad (37)$$

In the equation (36), L_l is the leakage inductance referred to the primary side [20]:

$$L_l = \frac{\mu_0 N_p{}^2 MLT b_w}{3 h_w p^2} \quad (38)$$

where p is the number of interfaces between winding sections and is given by twice the number of sections of the secondary winding [20]

$$P = \frac{2}{m} \frac{N_s}{N_{ls}} \quad (39)$$

In (39) m is a constant suggested by manufacturer. The voltage regulation constraint, for lagging power factor, can be approximated as [21]:

$$\frac{V_R + V_X}{E_p} \leq VR_m \quad (40)$$

In (40) VR_m is the maximum value of voltage regulation. The objective function can be written in terms of the primary variables by making use of the equations (12) to (15) as following:

$$f = 4K_f \rho_c c t h_w + 8K_f \rho_c c^2 t + 4K_f \rho_c c t b_w + 4K_{cu} \rho_{cu} t b_w h_w + \pi K_{cu} \rho_{cu} b_w{}^2 h_w \quad (41)$$

TABLE I. NUMERICAL VALUES OF THE PROBLEM

Parameter	Value	Parameter	Value
d	0.238(mm)	m	10
K_c	1.9×10^{-3}	ρ_w	$2.26\times10^{-8}(\Omega m)$
F_r	1.33	μ_0	$4\pi\times10^{-7}(H/m)$
β	2	μ_r	2000
α	1.24	ρ_c	$4800(Kg/m^2)$
B_{sat}	0.4T	K_a	40
ρ_{cu}	$8920(Kg/m^2)$	S	1200VA
E_p	300V	η_m	0.97
E_s	75V	VR_m	0.03
f	60Hz	K_φ	0.02
ΔT	$60C^0$	K_f	0.95
Pf	0.8lag	K_{cu}	0.6

II. SIMULATION

Numerical values of the problem is given in tables 1. Parameters of the PSO and HBB-BC algorithms are presented in Tables 2 and 3. In both algorithms, the value of the parameter γ related to the penalty-based method is 10. In power transformer optimization problem, the control variables are c, t, b_w, h_w, N_P, N_S, N_{lp},N_{ls}. Constraints stated with the equations 17, 20 and 22 are in quality form and constraints in equations 27, 28, 33, 34 and 40 are in inequality form.

Optimal values of the control variables which are obtained using the introduced algorithms as well as the results of the MOSEK software [2] are presented in Table 4.

TABLE II. PARAMETRS OF PSO ALGORITHM

Parameters	Value
N	50
K_{max}	20
C_1	1.5
C_2	2
ω_{max}	0.8
ω_{min}	0.3

TABLE III. PARAMETRS OF HBB-BC ALGORITHM

Parameters	Value
N	50
α_1	20
α_2	1.5
α_3	2
P_m	0.8
K_{max}	0.3

TABLE IV. RESULT OF THE DIFFERENT APPROACHES

Parameter	*HBB-BC*	*PSO*	*MOSEK*
c(cm)	0.5	0.51	0.49
t(cm)	2.19	0.43	2.21
b_w(cm)	0.64	0.63	0.68
h_w(cm)	2.38	2.41	2.44
N_p	38.12	39.1	38.18
N_s	9.48	9.3	9.55
N_{lp}	4	4	4
N_{ls}	1	1	1
$A_{cu,p}(mm^2)$	1.21	1.23	1.30
$A_{cu,s}(mm^2)$	5.19	5.33	5.21
m_c+m_{cu}(g)	148.69	163.92	157.74
η(%)	99.56	99.47	99.56
Time(sec)	0.52	0.71	0.67

As it is shown in Table 4, using proposed HBB-BC algorithm for designing transformer results in optimum and smaller dimensions of designed transformer in comparison to other approaches. Moreover the total mass of the designed transformer is less than other approaches. In addition to these advantages, efficiency of the designed transformer using HBB-BC algorithm is improved and time of the simulation is remarkably reduced.

In practical implementation of the designed transformer, the numbers of the primary and secondary winding turns, i.e. $N_p$and N_s will round up to 40 and 10, respectively.

Convergence characteristic of the objective function, which is considered total mass of the transformer, is presented in Fig. 2 while HBB-BC algorithm is applied for solving the optimization problem. In this figure, it is obvious that during progression of the algorithm, the

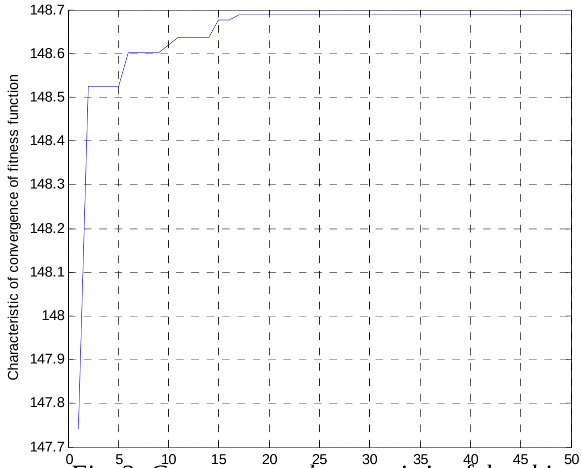
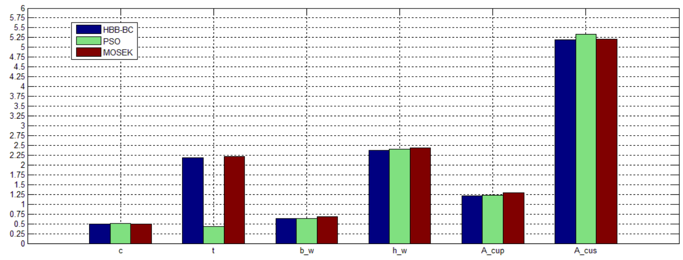


Fig. 2. Convergence characteristic of the objective function

A convergence characteristic of the objective function is meeting 148.69. Moreover optimized dimensions of the transformer using different methods are shown in Fig.3.



In this paper transformer optimization problem solved using hybrid big bang-big crunch (HBB-BC) algorithm aiming minimizing the core mass and winding mass with respect to satisfaction of the transformer constraints. The HBB-BC algorithm used the PSO algorithm capacities and mutation operator in order to improve the capabilities of the BB-BC algorithm and to avoid the trapping into the local optimum. Moreover simulation results of the HBB-BC algorithm is compared to the PSO algorithm and MOSEK software results. Simulation results has shown the effectiveness of the proposed algorithm for finding the global best and reducing the running time in comparison with the other methods. The HBB-BC algorithm minimized the mass of transformer core and wiring more than other mentioned methods.

REFERENCES

[1] G.Eason,B.Noble,andI.N.Sneddon,On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," Phil.Trans.Roy. Soc. London, vol.

[2] *R. A. Jabr, "Application of geometric programming to transformer design," IEEE Trans. Magn.,vol. 41, no. 11, pp. 4261-4269,Nov.2005.*

[3] P. H. Odessey, "Transformer design by computer," *IEEE Trans. Manuf. Technol.*, vol. MFT-3, no. 1, pp. 1–17, Jun. 1974.

[4] W. M. Grady, R. Chan, M. J. Samotyj, R. J. Ferraro, and J. L. Bierschenk, "A PC-based computer program for teaching the design and analysis ofdry-type transformers," *IEEE Trans. Power Syst.*, vol. 7, no. 2, pp. 709–717, May 1992.

[5] A. Rubaai, "Computer aided instruction of power transformer design in the undergraduate power engineering class," *IEEE Trans. Power Syst.*, vol. 9, no. 3, pp. 1174–1181, Aug. 1994.

[6] *Williams S.B., AbettiP.A.and Magnusson E.F., "Application of digital computers to transformer design" , AIEE Trans vol 75,part III, 1956,pp728-35*

[7] *Williams S.B, Abetti P.A and Mason H.J, "Complete design of Power transformers with a large size digital computer",AIEE Trans., 1959,vol77, PartIII,pp1282-91*

[8] *Adersen. W. , "Optimum design of electrical machines "'IEEE Transactions on Power Apparatus and Systems, 1967 PAS-86 (6)707-11*

[9] F. F. Judd and D. R. Kressler, "Design optimization of small low-frequency power transformers," *IEEE Trans. Magn.*, vol. MAG-13, no.4,pp. 1058–1069, Jul. 1977.

[10] W. G. Hurley, W. H. Wölfle, and J. G. Breslin, "Optimized transformer design: Inclusive of high-frequency effects," *IEEE Trans. Power Electron.*, vol. 13, no. 4, pp. 651–659, Jul. 1998.

[11] C. J. Wu, F. C. Lee, and R. K. Davis, "Minimum weight EI core and pot core inductor and transformer designs," *IEEE Trans. Magn.*, vol. MAG-16, no. 5, pp. 755–757, Sep. 1980.

[12] O. W. Andersen, "Optimized design of electric power equipment," *IEEE Comput. Appl. Power*, vol. 4, no. 1, pp. 11–15, Jan. 1991.

[13] L. H. Geromel and C. R. Souza, "The application of intelligent systems in power transformer design," in *Can. Conf. Electrical and Computer Engineering*, vol. 1, May 12–15, 2002, pp. 285–290.

[14] L. Hui, H. Li, H. Bei, and Y. Shunchang, "Application research based on improved genetic algorithm for optimum design of power transformers," in *Proc. Fifth Int. Conf. Electrical Machines and Systems*, vol. 1, Aug.18–20, 2001, pp. 242–245.

[15] Kennedy J, Eberhart RC. Particle swarm optimization. Proceeding of the IEEE International Conference on Neural Networks, 4,1995,1942-48.

[16] *Erol OK, Eksin I. A new optimization method: Big Bang–Big Crunch. Advances in Engineering Software2006;37(2):106-111.*

[17] *A. Kaveh and S. Talatahari, Size optimization of space trusses using Big Bang–Big Crunch algorithm, Computers and Structures87 (2009) 1129–1140.*

[18] N. Mohan, T. M. Undeland, and W. P. Robbins, Power Electronics: Converters, Applications and Design, 3rd ed. New York: Wiley, 2003.

[19] R. Petkov, "Optimum design of a high-power, high-frequency transformer,'' IEEE Trans. Power Electron., vol. 11, no. 1, pp. 33–42, Jan.1996.

[20] *P. H. Odessey, "Transformer design by computer.''IEEE Trans. Manuf.Technol., vol. MFT-3, no. 1, pp. 1–17, Jun. 1974.*

[21] S. J. Chapman, Electric Machinery Fundamentals, 3rd ed. Boston, MA: McGraw-Hill, 1999, pp. 90–92.