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DESIGN OPTIMIZATION OF POWER OBJECTS BASED ON CONSTRAINED NON-LINEAR MINIMIZATION, GENETIC ALGORITHMS, PARTICLE SWARM OPTIMIZATION ALGORITHMS AND DIFFERENTIAL EVOLUTION ALGORITHMS

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Abstract: This paper gives a detailed comparative analysis of Constrained non-linear minimization (CN), Genetic Algorithms (GA), Particle Swarm Optimization Algorithms (PSO) and Differential Evolution Algorithms (DE) results. The Objective Function that is optimized is a minimization dependent and all constraints are normalized and modeled as inequalities. The results demonstrate the potential of the DE Algorithm, shows its effectiveness and robustness to solve the optimal power object.

Key words: Constrained non-linear minimization, Genetic Algorithms, Particle Swarm Optimization, Differential Evolution, Arc Suppression Coil.

1. INTRODUCTION

The power objects designers face cumbersome routine calculations to achieve optimal constructions. Within a matter of minutes or even seconds, computers can generate a number of power objects designs (by changing current density, flux density, core dimensions, type of magnetic material and so on) and eventually come up with an optimal design [5]. The difficulty in resolving the optimum balance between the power object cost and its performance is becoming even more complicated nowadays, as the main power object materials (copper or aluminum for power object windings and steel for magnetic circuit) are stock exchange commodities and their prices vary daily. Techniques that include mathematical models containing analytical formulas, based on design constants and approximations for the calculation of the power object parameters are often the base of the design process used by power object manufacturers. [9, 19, 20, 21]

Differential Evolution Algorithm (DE) is a population based stochastic method for global optimization [1, 2, 3, 4, 6, 7, 8, 12, 13] for optimization problems over continuous domains. Constrained non-linear minimization (CN), Genetic Algorithms (GA), Particle Swarm Optimization Algorithms (PSO) and Differential Evolution Algorithms (DE) have been extensively used for solving combinatorial optimization problems. One area of great importance that can benefit from the effectiveness of such algorithms is electric energy distribution. The work in this paper introduces the use of CN, GA, PSO and DE applied to an arc suppression coil and comparing the calculated results [10, 14, 15, 16].

These approaches differ from other strategies focusing on the optimization on only one parameter of a power object performance (e.g., no-load losses or load losses). These methods are applied to the design of the arc suppression coil with several ratings and loss categories and the results are compared.

2. MATHEMATICAL MODELING AND OPTIMIZATION OF ARC SUPPRESSION COILS

A mathematical description of a global constrained minimization problem requires us to apply an appropriate model which has limited number of parameters (design variables) [11]. Any kind of optimization problem can be formalized to find the appropriate set of design variables in the multidimensional parameter space, which can optimize the main objective function [17, 18]. In the mathematical notation the optimization problem can generally be represented as a pair (S, f), where $S \subset R^n$ is a bounded set on R^n and $f : S \rightarrow R$ is an n-dimensional real-valued function. The problem is to find a point $\mathbf{x}_{min} \in S$ such that $f(\mathbf{x}_{min})$ is a global minimum on S. More specifically, it is required to find an $\mathbf{x}_{min} \in S$ such that

$$\forall \mathbf{x} \in S : f(\mathbf{x}_{min}) \leq f(\mathbf{x}) \quad (1)$$

$$g_i(\mathbf{x}) \leq 0, i = 1, 2, \bullet\bullet\bullet, q \quad (2)$$

$$h_j(\mathbf{x}) = 0, j = q + 1, \bullet\bullet\bullet, m \quad (3)$$

where $\mathbf{x} = [x_1, x_2, \bullet\bullet\bullet, x_n]^T$ is the vector of unknown quantities, $g_i(\mathbf{x})$ and $h_j(\mathbf{x})$ are the restriction constraints, which can be represented mathematically as equations or inequalities, m and q are integer numbers. Generally, for each variable x_i a constrained boundary should be satisfied

$$l_i \leq x_i \leq u_i, i = 1, 2, \bullet\bullet\bullet, n \quad (4)$$

Under these definitions, the optimization is focused on the minimization of the cost of the arc suppression coil's active part:

$$\min_{\mathbf{x}} \sum_{j=1}^{2} c_j \cdot f_j(\mathbf{x}) \quad (5)$$

where c_1 is the winding unit cost (€/kg), f_1 is the winding weight (kg), c_2 is the magnetic material unit cost (€/kg), f_2 is the magnetic material weight (kg), and $\mathbf{x}$ is the vector of the seven design variables, namely the width winding (a), the diameter of core leg (D), the winding height (b), the current density of winding (g), the magnetic flux density (B), variable air gap (δ_p) and fixed air gap (δ). It should be noted that functions f_1, f_2, appearing in the objective function (10) are composite functions of the design variables $\mathbf{x}$. The minimization of the cost of the arc suppression coil is subject to the constraints. The inequality constraints should be modified to the less or equal format, $g(x) \leq 0$.

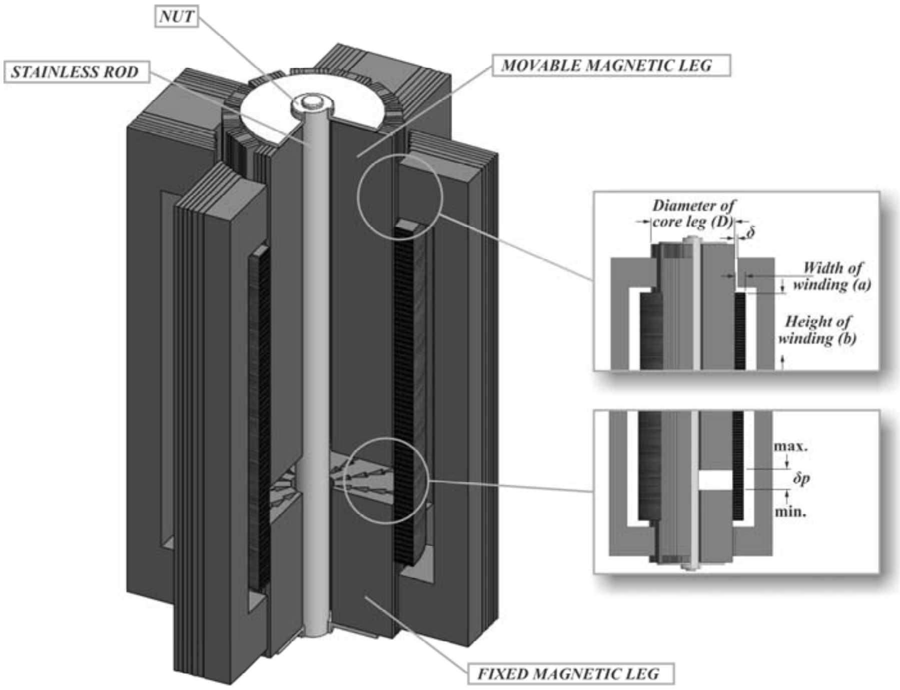

Fig. 1. Active part of arc suppression coil – main dimensions

$$53.0 \cdot x_1 \cdot x_2^2 \cdot x_3 \cdot x_4 \cdot x_5 \cdot 10^3 - 635 \leq 0 \tag{6}$$

$$\left(1.213 \cdot x_2 + 2.7 \cdot x_3 + 2.51 \cdot 10^{-2}\right) \cdot 10^{-7} \cdot x_3 \cdot x_4^2 \cdot x_5 - 5600 \leq 0 \tag{7}$$

$$\begin{aligned} &\left(-0.424 \cdot x_1^2 + 1.271 \cdot x_1 - 0.024\right) \cdot \\ &\left(\left(3.965 \cdot 10^4 \cdot x_5 + 2.405 \cdot 10^5 \cdot x_3 + 2.987 \cdot 10^3\right) \cdot x_2^2 + 1.892 \cdot x_2^3\right) \cdot 0.4 - 1800 \leq 0 \end{aligned} \tag{8}$$

$$\begin{aligned} &\left(4.84 \cdot x_3^2 \cdot x_4^2 x_5^2\right) / \\ &\left(10^4 \cdot x_6 / \left(6.9 \cdot x_2^2 \cdot \left(1 + 2.67 \cdot \left(x_6 / x_2\right)\right)\right) + 10^4 \cdot x_7 / \left(3.56 \cdot x_2^2 \cdot \left(1 + 5.26 \cdot \left(x_7 / x_2\right)\right)\right)\right) - 2.53 \leq 0 \end{aligned} \tag{9}$$

$$1 - x_6 \leq 0 \tag{10}$$

$$x_6 - 200 \leq 0 \quad (11)$$

$$6 - x_7 \leq 0 \quad (12)$$

$$x_7 - 16 \leq 0 \quad (13)$$

All inequality constraints are adjusted and modified in accordance with the requirements of the mathematical model in the form $g(x) \leq 0$.

Accordingly, the objective function for the model is:

$$f(x_2,x_3,x_5) = \left(2.29 \cdot 10^4 \cdot x_5 + 1.39 \cdot 10^5 \cdot x_3 + 1.73 \cdot 10^3\right) \cdot x_2^2 + 1.10 \cdot x_2^3$$
$$+\left(2.32 \cdot 10^5 \cdot x_2 + 4.75 \cdot 10^5 \cdot x_3 + 4.49 \cdot 10^3\right) \cdot x_3 \cdot x_5 \quad (14)$$

The constraints of the analyzed mathematical model are entered as follows: Constraint 6 matches to the arc suppression coil nominal rating, Constraint 7 - to the guaranteed load losses, Constraint 8 - guaranteed no-load losses and Constraint 9 - guaranteed inductance, Constraint 10 is the minimum of the variable air gap, Constraint 11 is maximum of the variable air gap, Constraint 12 is minimum of the fixed air gap, Constraint 13 is the maximum of the fixed air gap. Constants in front of decision variables have been taken from the Fig.1 and reference [15] and [16].

3. EXPERIMENTAL RESULTS

In order to find the global optimum design of an arc suppression coil, optimization approach techniques calculated based on CN and Evolutionary Algorithms GA, PSO and DE are used. The goal of the proposed optimization methods are to find a set of integer variables linked to a set of continuous variables that minimize the objective function (active part cost) and meet the restrictions imposed on the arc suppression coil design.

3.1. Differential Evolution Algorithm

The single objective Differential Evolution optimization algorithm with penalty function approach has been applied. The program has two input files, “Limits.txt” and “ParameterLimits.txt” and generates two output files, “ReportDE.html” and “Convergence.txt”. After inserting the objective function and constraints, the user needs to prepare the two input files (“Limits.txt” and “ParameterLimits.txt”). In the “Limits.txt” input file, the lower and upper bound for each decision variable separated by a tab, is entered. The number of decision variables for the analyzed mathematical model is seven.

Lower and Upper bound of decision variables in the “Limits.txt” input file for the analyzed mathematical model are: 1.16 up to 1.2 for the magnetic flux density (B) in Tesla, .3 up to .33 for the diameter of core leg (D) in m, .05 up to .06 for the width of secondary winding (a) in m, 3.2 up to 4.5 for the current density of secondary winding (g) in A/mm2, 0.5 up to 0.6 for the core window height (b) in m, 0.2 up to 20.0 variable air gap in cm and 0.6 up to 1.65 fixed air gap in cm.

The "ParameterLimits.txt" input file requires the number of decision variables, maximum number of generations, minimum and maximum number of population (NP), crossover constant (CR), weighting factor (F) along with their step length for sensitivity analysis in the third, fourth and fifth rows respectively.

The input file for the analyzed mathematical model is as follows: Number of decision variables is 10, Maximum number of generations is 30, Minimum, maximum and step length for NP 20, 20, 10, Minimum, maximum and step length for CR 0.8, 0.9, 0.1 and Minimum, maximum and step length for F 0.5, 0.6, 0.1.

The output figures in Table 1 are given for the analyzed mathematical model after the successful completion of the program [1].

Table 1.

Parameter	***Value***
X1	1.191886
X2	0.300710
X3	0.050218
X4	4.342104
X5	0.500434
X6	17.067546
X7	0.890047

Best Strategy is DE/rand-to-best/1/bin. Minimum constraint violation (CV): 0.0000E+000. Minimum objective value CV: 4.253416E+003. Minimum time taken: 31 ms

The parameters X_1, X_2, X_3, X_4, X_5, X_6, X_7 match respectively to the magnetic flux density (B), the diameter of core leg (D), the width winding (a), the current density of winding (g), the winding height (b), maximum variable gap in cm (δ_p) and minimum fixed air gap (δ) in cm, *Table 1*.

3.2. Constrained non-linear minimization using Matlab Optimization Toolbox

This calculus optimization approach finds minimum of a scalar function of several variables starting at an initial estimate. The general aim in constrained optimization is to transform the problem into sub-problems that can be solved and used as basis of an iterative process. These methods are now considered relatively inefficient and have been replaced by methods that have focused on the solution of the Karush-Kuhn-Tucker (KKT) equations. The KKT equations are necessary conditions for optimality of a constrained optimization problem.

For the purpose of this research we used the ' active-set ' algorithm which is not a large-scale algorithm. As a solver we used 'fminconfun' over the defined objective and nonlinear constrained function.

Total number of evaluations is 40 and the maximum constraint violation is 0. The low value shows that the solution is meaningful. Also, the optimization is completed because the objective function is non-decreasing in feasible directions and constraints are satisfied to within the default value of the constraint tolerance. The step size is 0.0114317 and the first-order optimality is 0.00883119. The Current Function Value is 4257.73.

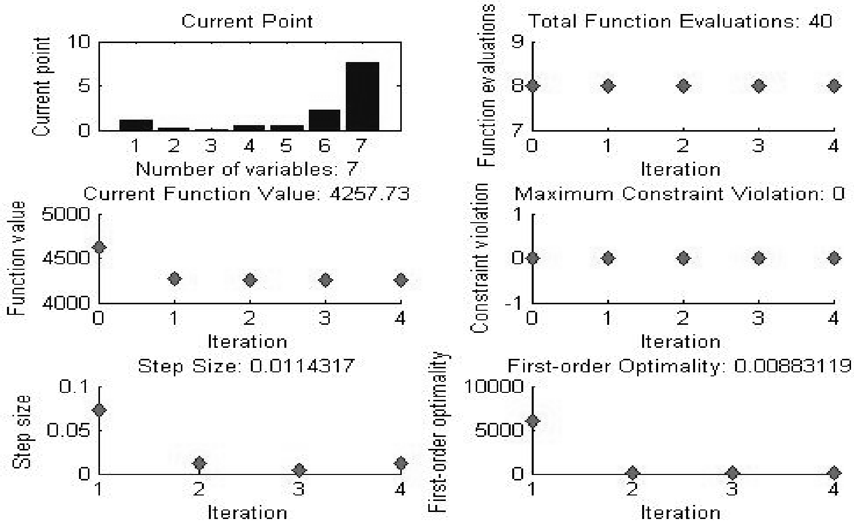

Fig. 2. CN-results, current function value

3.3. Optimization with Genetic Algorithm using Matlab Optimization Toolbox

Genetic Algorithms as class of stochastic search strategies modeled after evolutionary mechanisms, nowadays become a popular strategy to optimize non-linear systems with a large number of variables. GA theory provides a powerful mathematical framework in which we can find optimal value of some function.

The algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution.

The key question here is why to use GA instead of a classical algorithm. A classical algorithm generates a single point at each iteration and the sequences of points approach an optimal solution. Instead of this, a genetic algorithm generates a population of points at each iteration. The best point in the population approaches an optimal solution. With classically algorithmic approach the next point in the sequence is selected by a deterministic computation. Despite of this, the GA selects the next population by computation which uses random number generators.

Evaluation of the fitness and the constraint function is made in serial. A constraint tolerance of 1e-6 is used.

Optimization with GA was made in order to make comparative analysis of different optimization methods that are implemented in minimizing the objective function. The most important points in this approach are the evaluating fitness function and the selection rules and random behavior to select the next population. The Best Fitness value is 4264.71.

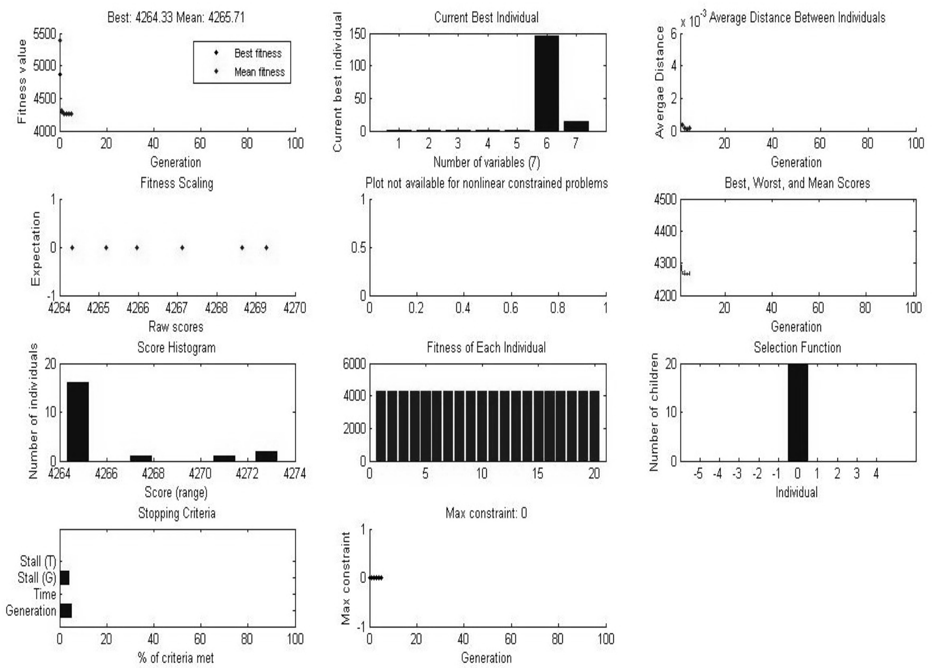

Fig. 3. GA-results, current function value

3.4. Optimization with Particle Swarm Optimization Algorithms (PSO)

The Particle Swarm Optimization Algorithms (PSO) is a population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling. The PSO has been successfully applied in many research, development and application area. In PSO, a swarm of n particles (individuals) communicate either directly or indirectly with one another search directions (gradients). Each particle is composed of three vectors and two fitness values. The particles never die in PSO and they can be seen as simple agents that fly through the search space and record (and possibly communicate) the best solution that they have discovered. The movement of a particle from one location to another, in the search space, is simply done by adding the new vector to the previous in order to get another vector, and also to evaluate and compare fitness in the new location. The Best Function Value is 4257.73.

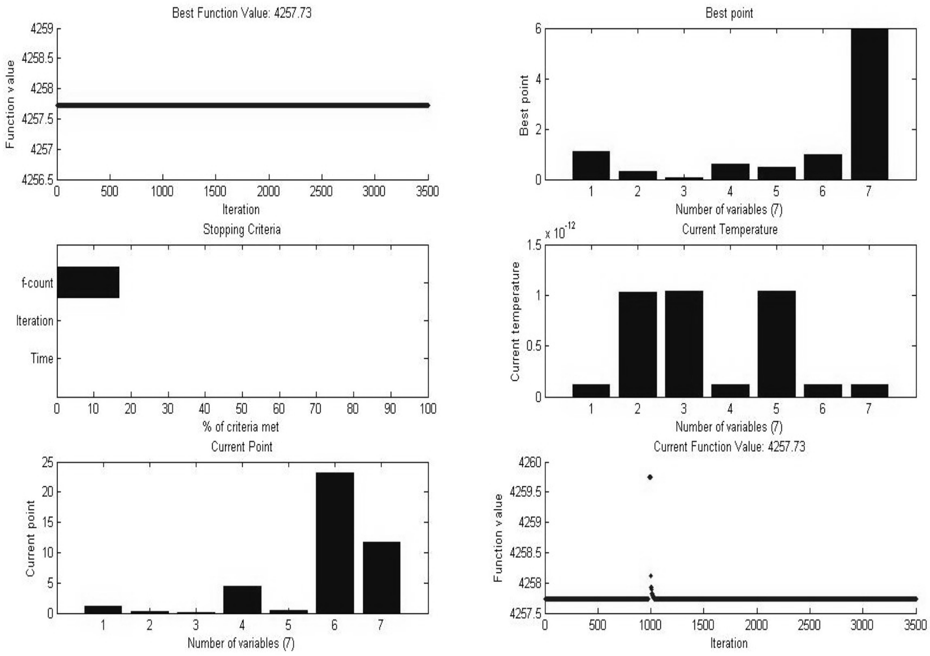

Fig. 4. PSO-results, best and current function value

4. CONCLUSION

In this paper, one of the recently proposed heuristic algorithms DE is used to solve the optimal cost problem with equality and inequality constraints in power objects. In this case, the minimization of active part cost is considered as objective function. This approach was successful in finding the optimal settings of the control variables of a test power object. The results proved the robustness and superiority of the DE approach to solve the optimal cost of an active part. Comparative results of the analyzed mathematical model with different optimization approaches are shown in Table 2.

Table 2.

Approach	*B*	*g*	*D*	*a*	*b*	Variable air gap	Fixed air gap	Active part
						min./max.	minimum	Cost
DE Alg.	1.192	4.340	301	50	500	1.6 / 17.07	0.89	4253.41
CN Alg.	1.188	4.289	301	50	500	1.8 / 18.10	0.81	4257.73
GA Alg.	1.192	4.305	301	50	500	2.0 / 18.06	0.78	4264.71
PSO Alg.	1.180	4.280	301	50	500	2.2 / 18.80	0.76	4257.73

The effectiveness of the DE algorithm is demonstrated and the observations revealed that the DE gives an optimal solution with less number of generations and requires less computation time.

REFERENCES

[1] A. Vasan, Optimization Using Differential Evolution. *Water Resources Research Report. Book 22. Department of Civil and Environmental Engineering*, The University of Western Ontario, Publication Date 7-2008.

[2] A. Zamuda, J. Brest, B. Bošković, V. Žumer. Differential Evolution with Self-adaptation and Local Search for Constrained Multi-objective Optimization. *IEEE Congress on Evolutionary Computation (CEC)*, 2009, pp. 195-202.

[3] J. Brest, A. Zamuda, B. Bošković, V. Žumer. Dynamic Optimization using Self-Adaptive Differential Evolution. *IEEE Congress on Evolut. Computation (CEC)*, Trondheim, Norveška, 2009, pp. 415-422.

[4] DE Homepage. http://www.icsi.berkeley.edu/~storn/code.html

[5] Onwubolu, G. C., and Babu, B. V. *New Optimization Techniques in Engineering*. Springer-Verlag, Germany, 2004.

[6] P.V. Kenneth., S.M. Rainer. Differential evolution - A simple evolution strategy for fast optimization. *Dr. Dobb's Journal*, 1997, 22, 18-24 and 78.

[7] P.V. Kenneth., S.M. Rainer., L.A. Jouni. Differential evolution: A practical approach to global optimization. Springer-Verlag, Berlin, Heidelberg, 2005.

[8] B.V. Babu, M. Mathew, L. Jehan . Differential Evolution for Multi-Objective Optimization. *Chemical Enginering Department B.I.T.S.* Pilani, India, 2005.

[9] E.I. Amoiralis, P.S. Georgilakis, M.A. Tsili . Design optimization of distribution transformers based on mixed integer programming methodology. Technical University of Athens, Greece, 2008.

[10] R. Salkoski. Selection of an optimal variant of 3-phase transformers with round and rectangular section of the magnetic core from aspect of minimum production costs. *Master Thesis, Electrotechnical University in Skopje*, 2000.

[11] Mezura and Montes.: E. Laboratorio NI Avanzada, Rébsamen 80, Centro, Xalapa, Veracruz 91090, Mexico, Velazquez-Reyes, J., Coello Coello, C.A. Modified Differential Evolution for Constrained Optimization , *Conference Publications, Evolutionary Computation, CEC*, 2006, pp 25 – 32.

[12] U.K. Chakraborty (Ed.). *Advances in Differential Evolution, Mathematics & Computer Science Department*, University of Missouri, St.Louis, USA, Springer-Verlag Berlin Heidelberg, 2008.

[13] J. Rönkkönen, S., Kukkonen, K. V. Price.: Real-parameter optimization with differential evolution. *Proc. IEEE Congr. Evolut. Comput*., Sep. 2005, pp. 506–513, Edinburgh, Scotland (2005).

[14] R. Salkoski, I. Chorbev. Design optimization of distribution transformers based on Differential Evolution Algorithms. *ICT Innovations 2012*, ISSN 1857-7288, Ohrid, 2012, pp.35-44.

[15] R.Salkoski, Design and tests of high voltage reactors. The Fourth Conference MAKO CIGRE, A2-08 , September, Ohrid 2004.

[16] R.Salkoski, Arc Suppression Coils with adjustable gap. The First Conference MAKO CIGRE, STK 12 , P12-01, Struga, 1996.

[17] S.Wang, Y. Duan, W. Shu, D.Xie, Y.Hu, Z,Guo. Differential Evolution with Elite Mutation Strategy. *J. of Comput. Inform. Sys*. 9:3, 2013, pp.855-862.

[18] F.S.Lobato,R.Gedraite,S.Neiro. Solution of Flow Shop Problems using the Differential Evolution Algorithm. *EngOpt 2012-3rd ICEO*, Rio de Janeiro, Brazil, 01-05, 2012.

[19] S.K.Morya,H.Singh. Reactive Power Optimization Using Differential Evolution Algorithm. *IJETT-Volume 4 Issue 9*, 2013.

[20] A.Lotfi, M.Faridi. Design Optimization of Gapped-Core Shunt Reactors. *IEEE Transactions on Magnetics.* Vol.,48,No. 4, 2012.

[21] A.Lotfi, E. Rahimpour. Optimum design of core blocks and analyzing the fringing effect in shunt reactors with distributed gapped-core. *ELSEVIER, Electric Power Systems Research* 101, 2013, pp.63-70.

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