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MODIFIED PARAMETER OPTIMIZATION OF DISTRIBUTION TRANSFORMER DESIGN USING COVARIANCE MATRIX ADAPTATION EVOLUTION STRATEGY.

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Abstract
Optimal transformer design (TD) is a complex multi-modal, multi-objective, mixed-variable and non-linear problem. This paper discusses the application of Covariance Matrix Adaptation Evolution Strategy (CMA-ES) for distribution TD, minimizing four objectives; purchase cost, total life-time cost, total mass and total loss individually. Two independent variables; voltage per turn and type of magnetic material are proposed to append with the usual TD variables, aiming at cost effective, reduced weight, and energy efficient TD. Three case studies with three sets of TD vectors are implemented on 400 KVA, 20/0.4 KV transformer to demonstrate the superiority of Modified Design Variables (MDV), in terms of cost savings, material savings, and loss reduction. Simulation results of CMA-ES provide better TD on comparison with conventional transformer design procedure, branch and bound algorithm tailored to a mixed-integer non-linear programming, Self Adaptive Differential Evolution (SaDE), and real coded GA (RGA). Statitical analysis has proven the faster convergence and consistency of CMA-ES. Moreover, NSGA-II is applied for solving multi-objective TD optimization problem with the aim of providing tradeoff between conflicting TD objectives.

Introduction

All power utilities are much worried about the high failure rate of distribution transformers. Transformers can be expected to operate 20–30 years. But losses in the form of heat reduce the transformer life by causing damage to the insulation. Finding ways to decrease the losses of the transformer is an important factor in reducing transformer failure rate, costs, and CO2 emissions. Total lifetime cost (TLTC) is the total life cycle cost which considers the future operating costs of a unit over its lifetime, brought back into present-day cost and then added to its total purchase price. A transformer with low TLTC is expected to have low losses and a longer life. Selecting energy-efficient distribution transformers ‘SEEDT’ project also concluded that electricity distribution companies and commercial and industrial users should use the TLTC method for making transformer purchasing decisions. Energy-efficient transformers are more expensive, but use less energy, resulting in lesser TLTC [1]. So designing a transformer based on purchase cost, without considering the future losses is therefore not the right decision. TD based on minimizing TLTC alone can drop off the transformer failure rate by reducing losses, amount of power generation needed to accommodate the losses, operating cost, emission of greenhouse gases and environmental cost, among the other TD objectives.

Nomenclature

TD transformer design
CMA-ES Covariance Matrix Adaptation Evolution Strategy
TLTC total life time cost
MIP mixed integer programming
FEM finite element method
BBA branch bound algorithm
BEM boundary element method
BBA-MINLP BBA-mixed integer non-linear programming
BFA bacterial foraging algorithm
MC manufacturing cost
MM magnetic material
TMM type of magnetic material
GA genetic algorithm
CTDP conventional transformer design procedure
LV low voltage
HV high voltage
MDV Modified Design Variables
SD Standard Deviation
CT computation time
*NA not applicable
LMT length of mean turn
EAs evolutionary algorithms
SaDE Self Adaptive Differential Evolution
RGA Real coded Genetic Algorithm
MOP multi-objective optimization problem
MOEAs Multi-Objective EAs
POF Pareto Optimal Front
NSGA-II non-dominated sorting genetic algorithm-II
CMA Covariance Matrix Adaptation
ES Evolution Strategy

Symbols
P_{GNLL} guaranteed no-load loss in Watts
P_{GLL} guaranteed load loss in Watts
U_{ks} guaranteed short circuit impedance in percentage
e_1 IEC standard tolerance for no-load and load loss constraints in %
e_2 IEC standard tolerance for total loss and impedance voltage constraints in %
$C_{FE,i=1,..10}$ unit cost of *i*th magnetic material in Euro per kg
C_{COND} unit cost of conductor in Euro per kg
C_{SS} unit cost of sheet steel in Euro per kg
C_{OIL} unit cost of mineral oil in Euro per kg
C_{INS} unit cost of insulating paper in Euro per kg
C_{DS} unit cost of duct strips in Euro per kg
C_{CORR} unit cost of corrugated panel in Euro per kg
$\boldsymbol{x}_{t=1,2..n}$ *t*th design variable
$z_{p=1,...,4}$ *p*th objective function
$h_{j=1,2..q}$ *j*th inequality constraint
$G_{FE,i=1,..10}$ weight of *i*th magnetic material in kg
G_{LV} weight of LV conductor in kg
G_{HV} weight of HV conductor in kg
G_{SS} weight of sheet steel in kg
G_{OIL} weight of mineral oil in kg
G_{INS} weight of insulating paper in kg
G_{DS} weight of duct strips in kg
G_{CORR} weight of corrugated panel in kg
C_{TM} total main materials cost of transformer in Euro
C_{TLT} total life time cost of transformer in Euro
T_{wt} total mass of transformer in kg
T_{los} total loss of transformer in Watts
C_{rem} cost of transformer remaining materials in Euro
C_{lab} labor cost in Euro
AA no load loss cost rate in Euro per Watts
P_{NLL} designed no-load loss in Watts
BB load loss cost rate in Euro per Watts
P_{LL} designed load loss in Watts
S_m sales margin in percentage
$\boldsymbol{dv}_{i=1..3}$ design vector
ov output variables
U_k designed short circuit impedance in percentage
T_{cl} thickness of core leg in mm
H_{diss} total heat dissipated by convection and radiation through cooling arrangement.
$\boldsymbol{C}^{(g)}$ covariance matrix '**C**' at generation g
N normal search distribution
$\sigma^{(g)}$ overall standard deviation; step size at generation g
$m^{(g)}$ mean value '*m*' of the search distribution at generation g
$\boldsymbol{R}^n$ linear transformation
n search space dimension, i.e., number of decision variables
g iteration number
$\boldsymbol{X}_k^{(g+1)}$ *k*th offspring from generation g + 1; search point
λ number of sampling points
μ number of selected best individuals in the population
$p_c^{(g)}$ evolution path at generation g
$p_\sigma^{(g)}$ conjugate evolution path at generation g
FF fitness function
g_{max} maximum number of generations
z^{max} objective function value of the worst feasible solution
$z(x)$ objective function value of the feasible solution
$err_j(x)$ normalized constraint violation
$Feval$ Maximum number of function evaluations
$\boldsymbol{H}$ Hessian matrix
$\boldsymbol{P}_t$ parent population of MOP
$\boldsymbol{Q}_t$ offspring population of MOP
$\boldsymbol{R}_t$ combined population of MOP
$f_{i=1...M}$ '*M*' objective function values of MOP
Np population size in MOP problem

But this TLTC minimization objective is rarely attended in most of the kinds of literature. From the overview of research papers in TD, efforts are focusing on the prediction of specific transformer characteristics, techniques adopted for transformer design optimization, transformer post design performance and modeling and recent trends on transformer technology. In a nutshell, TD optimization problem remains an active area [1]. TD optimization can be the minimization of no-load loss [2,3], minimization of load loss [4], maximization of efficiency [5–8], maximization of rated power [9], minimization of mass [9] or minimization of cost [5,6,10–19], based on the objective functions. A comparison of non-linear programming techniques for the optimum design of transformers was presented in [20]. Optimization is done by geometric programming for the minimization of the total mass of the transformer, [9] provided a solution for low and high-frequency transformers. But this method finds difficulty in combination with the cost estimation algorithm and requires a mathematical model.

Mixed integer programming (MIP) in combination with finite element method (FEM) [10], MIP in combination with branch bound algorithm (BBA) [11], bacterial foraging algorithm (BFA) [5] and simulated annealing technique [12] have been adopted for the minimization of main material cost (CTM) of transformer, without considering the transformer losses. However, all these methods have got their own drawbacks. MIP-FEM is sensitive to the selection of the value range of design variables and fails to find the global optimum. MIP-BBA is time-consuming since the number of nodes in a branching tree is too large. The drawbacks of the simulated annealing technique are finding difficulty in extending itself to the multi-objective case and long searching time to find the optimum. When the search space and complexity grow exponentially in scalable problems, basic BFA would not be suitable. Hybrid FEM with boundary element method (BEM) [21], trial and error based heuristic approach [13] have been implemented for the minimization of transformer manufacturing cost (MC), which is the mere sum of CTM and labor cost, excluding the operational cost.

BBA tailored to mixed-integer non-linear programming (MINLP) [15], numerical field analysis technique in combination with BEM [19] and multiple algorithm based hybrid approach [23] have addressed the minimization of TLTC of the transformer. These papers have overcome the above-said weaknesses, by including losses in the objective function calculation. But the numerical field analysis technique has the disadvantage of complex mesh size in 3D configurations [22]. Besides, the minimization of only one TD objective is considered [19,23] resulting in a single solution, which may not suit the requirements of all the categories of decision-makers. The type of magnetic material (TMM) is also not utilized as a design variable in the optimization process [15,19,23].

A novel gamma approach [24] and BFA based optimal design [6] have been proposed for solving the multi-objective TD optimization problem. But the authors failed to consider a three phase transformer and have not taken TLTC as one of the TD objectives. Generally, the objective functions of the TD problem are no differentiable, non-convex, mixed-variable, non-linear, and multi-modal and it is very difficult to obtain an optimal solution. Furthermore, TD calculations require access to several look-up tables' data for the evaluation of specific core loss at various flux densities, winding gradient, oil gradient, and heat transmission. Such complex analytical calculations interacting with graphical data are not handled accurately by the derivative based methods discussed above and thus the optimal solution is not guaranteed for the TD optimization problem solved by the analytical methods. Apart from the deterministic methods, soft computing techniques such as genetic algorithm (GA) and neural network are also employed for the TD optimization. GA has been applied for the minimization of MC, incorporating TMM as design variable [14], transformer cost plus running cost minimization [16,17], and optimal placement of distribution transformers [18]. Neural network technique has been applied for the prediction and minimization of power losses [22], and minimization of no load loss [2,3]. But these papers used single optimization method for TD which limited the optimization performance of their approach. A more recent approach to adapting the search direction is the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) proposed by Hansen and Ostermeier [25]. Its important property is invariance against the linear transformations in the continuous search space, when compared to other evolutionary algorithms (EAs).

CMA-ES is a continuous (real-parameter) EA that generates new population members by sampling from a probability distribution that is constructed during the optimization process. Owing to the learning process, CMA-ES is invariant to rotation and scaling of the coordinate system, reliably adapts well to ellipsoidal functions, and significantly improves convergence rate especially on non-separable and/or badly scaled objective functions. CMA-ES thus finds a global or near optimal minimum without using derivatives of the objective functions. CMA-ES is a strong optimizer that outperformed its other similar learning algorithms in CEC2005 benchmark functions and BBOB-2009 . Hence in this paper CMA-ES is applied for solving this complex TD optimization problem.

The main contributions of the paper are: (a) application of CMAES for TD optimization for the first time, assuring accuracy, consistency and convergence; (b) incorporation of TMM as one of the design variables for representing 10 different materials; (c) inclusion of variable, voltage per turn in place of low voltage (LV) turns; (d) implementation of three case studies to show the superiority of MDV; (e) optimization of four different objectives such as minimization of purchase cost, minimization of TLTC, minimization of total mass, and minimization of total loss, individually suggesting the designer a set of optimal transformers instead of single solution, so that he can choose which of them best fits the requirement of the customer and application under consideration; (f) comparison of simulation results with recent report [15], conventional transformer design procedure (CTDP) , Self Adaptive Differential Evolution (SaDE), and Real coded Genetic Algorithm (RGA); (g) use of multi-objective TD optimization using NSGA-II.

This paper is organized as follows: Sections Design of distribution transformer, CMA-ES algorithm an overview, CMA-ES based TD optimization, Multi-objective TD optimization, Computational results and Conclusion the paper

Design of distribution transformer

Preliminary input for TD The design procedure is presented for a three-phase oil-immersed shell-type wound core distribution transformer. The specified information consists of desired input variables required for the transformer design employing analytical formulae to calculate the transformer parameters. These transformer variables include transformer rating, design requirements on guaranteed no-load loss (PGNLL), guaranteed load loss (PGLL), guaranteed short circuit impedance (Uks), minimum full-load efficiency, maximum temperature rise, voltage regulation, tolerances e1, (e2), core stacking factor, mass density of core, magnetization curve of the magnetic material (MM), specific core loss data [30] for various maximum magnetic flux densities at 50 Hz frequency for 10 magnetic materials (M3-0.27, M4-0.27, MOH-0.23, MOH-0.27, 23ZDKH90, 23ZH90, 23ZH95, 27ZDKH95, 23ZDMH85, and 27ZDMH), resistivity of the conductor material (copper) at the maximum specified temperature, type of internal and external winding, typical practical values for insulation of conductor, distance and insulation between windings and core, mass density of conductor, distance between two adjacent cores, maximum ambient and winding temperature, direction space factor for turns and layer, HV taps, etc. The copper sheet is used for LV conductor and copper wire is used for HV conductor.

CMA-ES algorithm an overview

Evolution strategies (ES) are stochastic, derivative-free methods for numerical optimization of non-linear problems. CMA-ES is an efficient ES for problems for which derivative-based methods are unsuccessful, due to rugged search space with multiple discontinuities, sharp bends, and local optima. This algorithm is analogous to the gradient-based quasi-Newton method. CMA-ES has emerged as a very competitive real-parameter optimizer for continuous search spaces. It adapts two unique principles; maximum likelihood principle and two evolution paths and thus distinct from other ES. It is a continuous EA that generates new population members by sampling from a multivariate normal distribution N(m, C) constructed by its mean value, m e Rn and its symmetric positive definite covariance matrix, C e Rnxn during the optimization process. ‘m’ of the distribution determines the translation displacement and gets updated such that the likelihood of previous successful candidate solutions is maximized. ‘C’ has a geometrical interpretation, can be uniquely identified with the iso-density ellipsoid. ‘C’ determines the shape of the distribution ellipsoid, whose principal axes are eigenvectors of ‘C’ and squared axes lengths are eigenvalues. This algorithm exploits two adaptation mechanisms; Covariance Matrix Adaptation (CMA) and step size (r) adaptation.

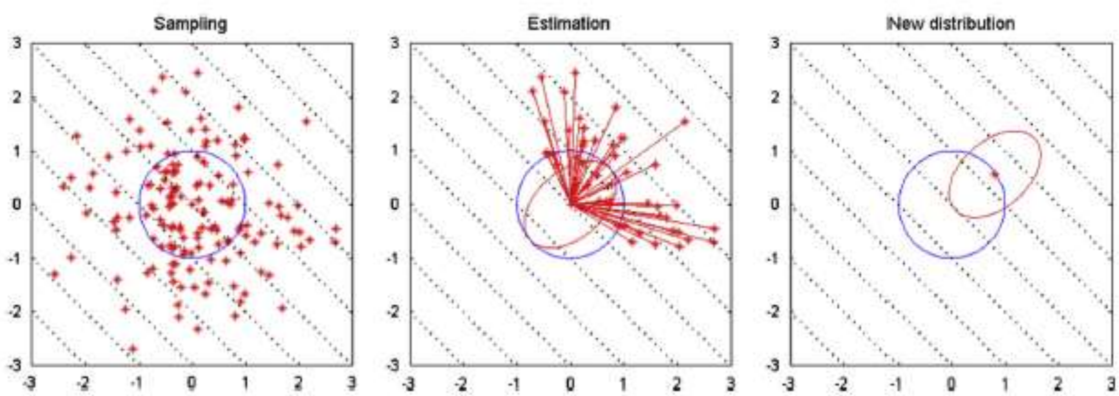

Fig. 1. Estimation of the covariance matrix

NSGA-II

The steps involved in the working of NSGA-II are given below.

Step 1: Initially generate a random parent population, Pt of size Np at generation ‘t’.

Step 2: Calculate all the objective function values separately for the entire population. Sort the population-based on non-domination levels.

Step 3: Assign a rank for each solution based on its non-domination level.

Step 4: Apply the binary tournament selection, Simulated Binary Crossover (SBX) crossover, and polynomial mutation operators on Pt and create an offspring population Qt of size Np.

Step 5: Combine parent and offspring populations to implement elitism and form an intermediate population, Rt of size 2Np.

Step 6: Evaluate the fitness for 2Np population solutions using multiple objective functions.

Step 7: Perform non-dominated sorting over the 2Np population to rank and divide the individuals into different POFs. Assign rank for the POFs in such a way that the first non-dominating POF with rank one and so on.

Step 8: Calculate the crowding distance of all the solutions. Higher the value of crowding distance better is the probability of the solution to be selected for the next generation.

Step 9: Select Np member for the new population Pt+1 from the combined population 2Np, on the basis of ranking and crowding distance. i.e., choose individuals of the best low ranked POFs first followed by the next best POF and so on. In case there is space only for a portion of a POF to accommodate in the new population, choose individuals among those in the front that are from the least crowded regions (determined by a crowded-distance operator and fill up the required number in the new population, Pt+1.

Step 10: Form the parent population for the next generation Pt+1.

Step 11: Check if the termination criteria are met. If yes, get the Pareto optimal solution. Else go to step 4.

Computational results

To demonstrate the effectiveness of the proposed MDV, a design example of 400 KVA, 50 Hz, 20/0.4 kV, 3 phase, shell type, wound core transformer with vector group, Dyn11 has been considered. The upper and lower bounds of the design variables, AA, BB, unit price of transformer materials Crem, Clab, Sm, e1 = 15%, e2 = 10% are derived from [15]. As reference transformer, the transformer with loss category AB0 according to CENELEC is selected, which means that PGNLL = 750 W, PGLL = 4600 W, and Uks = 4%. Coding for TD optimization is developed using MATLAB 7.4 on Intel core, i3 processor Laptop, operating at 3.2 GHZ, with 3 GB RAM. Suitable modifications are incorporated for handling TD constraints in the coding of CMAES algorithm. The population size and a maximum number of function evaluations are fixed at 100 and 10,000 respectively.

Conclusion

In this paper, CMA-ES algorithm is employed for the optimum design of a three-phase distribution transformer. The work proposed aiming at contributing a TD that minimize the objective(s) such as purchase cost, total life-time cost, total mass, and total loss of the transformer using proposed MDV, taking into account the constraints imposed by the international standards, transformer specifications, and customer needs. The validity of the CMA-ES algorithm for solving TD optimization problem is illustrated by its application to a 400 KVA distribution transformer design and comparison of its simulation results with CTDP, BBA-MINLP method, SaDE, and RGA. The significance of MDV for all the TD objective functions and have proven that MDV is efficient for the TD optimization problem. The proposed MDV is not only capable of producing optimum design but also render considerable cost savings, material savings, and loss reduction. Statistical analysis has clearly demonstrated the effectiveness of CMA-ES with respect to its global searching, solution precision, consistency in obtaining solutions, and faster convergence. Thus it is evident that CMA-ES with dv3 is able to give the least purchase cost (z1), TLTC (z2) with cost savings of about 10%, 6% and, 17%, 5% respectively on comparison with BBA-MINLP method [15] and CDTP. This paper has also dealt with the solution of TD MOP using NSGA-II with the tradeoff between purchase cost and TLTC. The best compromise solution obtained by fuzzy set theory for the multi-objective TD optimization gives a much better transformer design than the one obtained by single objective TD optimization using CMA-ES, by saving 1785 Euros of TLTC, which is accepted by SEEDT as an energy-efficient TD objective.

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