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 mixedinteger 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 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

CMA-ESCovariance Matrix Adaptation Evolution StrategyGravregistr of HV conductor in kgTLTCtotal life time costGravweight of HV conductor in kgTLTCtotal life time costGravweight of Strates testel in kgMPmixed integer programmingGravweight of ducts trips in kgEMboundary element methodGravweight of ducts trips in kgBA-MINLPBA-mixed integer non-linear programmingGravweight of curstrais cost of transformer in EuroFAbacterial foraging algorithmGravtotal main materials cost of transformer in EuroMCmanufacturing costTwetotal mass of transformer in WattsCAgenetic algorithmGrawcost of transformer in WattsCAgenetic algorithmGrawcost of transformer in WattsCTDPconventional transformer design procedureAtno load loss cost rate in Euro per WattsLVlow voltageBbload loss cost rate in Euro per WattsLVlow voltageBbload loss cost rate in Euro per WattsDSstandr DeviationSmsales margin in percentageCTcomputation time M_{t-13} design voctorMNmagnetic materialLyoutput variablesDSStandard DeviationSmsales margin in percentageCTcomputation time M_{t-13} design voctorMNwatterBaload loss cost race in Euro per WattsDSStandard DeviationSmsales margin in perce	TD	transformer design	Gov	weight of IV conductor in kg
TLTC total life time cost and the programming total models where the programming total life time cost and the programming total models of the programming total mass of transformer in the	CMA-FS	Covariance Matrix Adaptation Evolution Strategy	Gun	weight of HV conductor in kg
MIP mixed integer programming Gott weight of mineral oil in kg PEM finite element method Gott weight of mineral oil in kg BBA boundary element method Gott weight of functarial paper in kg BEM boundary element method Gott weight of functarial paper in kg BEA-MINLP BA-mixel method Gott weight of functarial paper in kg BEA-MINLP BA-mixel method Gott weight of functarial paper in kg BEA-MINLP BA-mixel method Gott The cost of transformer in kg MIM magnetic material Twe total main materials cost of transformer in kg TMM type of magnetic material Gott Gott cost of transformer in kg CTDP conventional transformer design procedure A no load loss cost rate in Euro per Watts HV high voltage BB load loss cost rate in Euro per Watts MDV Molif Design Variables Plit designed host circuit impedance in percentage MT ength of mean turn Uk designed host circuit impedance in percentage MOP mothodicaperition problem Cotal heast dissipated by convecti	TITC	total life time cost	Gree	weight of sheet steel in kg
FEMfinite element method $G_{\rm BS}$ weight of insulating paper in kgBBAbranch bound algorithm $G_{\rm BS}$ weight of corrugated panel in kgBBAbranch bound algorithm $G_{\rm DS}$ weight of corrugated panel in kgBBA-MINLPBA-mixed integer non-linear programming $G_{\rm RT}$ total line time cost of transformer in EuroBFAbacterial foraging algorithm $G_{\rm RT}$ total line time cost of transformer in kgMCmanufacturing cost $T_{\rm wer}$ total line time cost of transformer in WattsMMmagnetic material $G_{\rm em}$ cost of transformer remaining materials in EuroGAgenetic algorithm $G_{\rm men}$ cost of transformer remaining materials in EuroGAgenetic algorithm $G_{\rm men}$ cost of transformer remaining materials in EuroCTPconventional transformer design procedureAhno load loss cost rate in Euro per WattsLVlow voltage $P_{\rm HL}$ designed no-load loss in WattsSDStandard Deviation $S_{\rm m}$ sales margin in percentageCTcomputation time $d_{\rm FL1}$ designed load loss in WattsSDStandard Deviation $S_{\rm m}$ sales margin in percentageLMTlength of mean turn U_k designed short circuit impedance in percentageLASevolutionary algorithm $G_{\rm H}$ covariance matrix 'C at generation gNOEASMulti-Objective potimization problem $G_{\rm H}$ ovariance matrix AdaptationMDFmalti-objective coptimization problem </td <td>MIP</td> <td>mixed integer programming</td> <td>Gou</td> <td>weight of mineral oil in kg</td>	MIP	mixed integer programming	Gou	weight of mineral oil in kg
BBA branch bound algorithm G _{DS} weight of duct strips in kg BEA boundary element method G _{DS} weight of duct strips in kg BEA-MINLP BA-mixel integer non-linear programming G _{TT} total main materials cost of transformer in Euro DK manufacturing cost Tw total mass of transformer in kg MM magnetic material Tw total mass of transformer in Watts TMM type of magnetic material Cw cost of transformer remaining materials in Euro CA genetic algorithm Cw cost of transformer remaining materials in Euro CDP conventional transformer design procedure AA no load loss cost rate in Euro per Watts LV low voltage Phut designed load loss in Watts SD Standard Deviation Sm sales margin in precentage CT computation time Ov output variables LMT length of mean turn Uk designed short circuit impedance in percentage CA evolution mated sorting genetic algorithm Td thickness of core leg in mm SDE SEA daptive Differential Evolution Haits thickness of core leg	FEM	finite element method	GINE	weight of insulating paper in kg
BEMboundary element method G_{COR} weight of corrugated panel in kgBBA-MINLPBRA-mixed integer non-linear programming G_{rorm} total minimaterials cost of transformer in EuroBFAbatchrail foraging algorithm G_{rorm} total life time cost of transformer in EuroMCmanufacturing cost T_{ror} total life time cost of transformer in kgMMmagnetic material T_{ror} total loss of transformer in WattsTMMtype of magnetic material C_{men} cost of transformer remaining materials in EuroGAgenetic algorithm C_{men} cost of transformer remaining materials in EuroGAgenetic algorithm C_{men} cost of transformer remaining materials in EuroIVlow voltage P_{tut} designed no-load loss in WattsIVlow voltage P_{tut} designed no-load loss in WattsMDVModified Design Variables P_{tut} designed load loss cost rate in Euro per WattsSDStandard Deviation S_{m} sales margin in percentageMDVModified Design Variables P_{tut} designed short circuit impedance in percentageMTlength of mean turn U_k designed short circuit impedance in percentageRAnot applicable Ov output variablesSDESelf Adaptive Differential Evolution H_{diss} MDEAsMulti-Objective optimization problem $O^{(d)}$ MDEAsMulti-Objective EAsNPOFPareto Optimal Front $O^{(d)}$	BRA	branch bound algorithm	Gos	weight of duct string in kg
BBA-MINLP BBA-mixed integer non-linear programming Gm total main materials cost of transformer in Euro BFA bacterial foraging algorithm Gm total main materials cost of transformer in Euro BFA magnetic material Tmr total main materials cost of transformer in Mg MM magnetic material Tmr total mass of transformer in Watts TMM type of magnetic material Tmr total loss of transformer in Watts CTDP conventional transformer design procedure A no load loss cost rate in Euro per Watts V woltage Prut designed loss cost rate in Euro per Watts MDV Modified Design Variables Prut designed load loss in Watts SD Standard Deviation Sm sales margin in percentage CT computation time dureta designed short circuit impedance in percentage LMT length of mean turn Uk designed short circuit impedance in percentage LMT length of mean turn Cf covariance matrix 'C at generation g MOP multi-objective optimization problem Cf covariance matrix dapticable DVF Pareto Optimal Front	BEM	boundary element method	GCOPP	weight of corrugated papel in kg
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$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	BFA	bacterial foraging algorithm	Спт	total life time cost of transformer in Euro
MMmagnetic materialTasktotal loss of transformer in WattsTMMtype of magnetic materialTasktotal loss of transformer remaining materials in EuroGAgenetic algorithmGablabor cost in EuroCTDPconventional transformer design procedureAAno load loss cost rate in Euro per WattsIVlow voltage P_{HL} designed no-load loss in WattsIVlow voltage P_{HL} designed no-load loss in WattsMDVModified Design Variables P_{LL} designed no-load loss in WattsSDStandard Deviation S_m sales margin in percentageCTcomputation time dv_{r-1-3} designed short circuit impedance in percentageLMTlength of mean turn U_k designed short circuit impedance in percentageEAsevolutionary algorithms T_d thickness of core leg in mmSaDESelf Adaptive Differential Evolution H_{diss} total heat dissipated by convection and radiationMOPmulti-objective optimization problem $C^{(g)}$ covariance matrix 'C at generation gMOEAsMulti-Objective EAsNnormal search distributionPOFPareto Optimal Front $\sigma^{(g)}$ overall standard deviatin; step size at generation gESEvolution Strategynsearch space dimension, i.e., number of decision variablesguaranteed load loss in Watts g_{g-1} the dispring from generation g + 1; search point u_{kl} uaranteed load loss in Watts g_{g-1} $guaranteed lo$	MC	manufacturing cost	Tur	total mass of transformer in kg
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$\begin{array}{cccccccccccccccccccccccccccccccccccc$	GA	genetic algorithm	Ciab	labor cost in Euro
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CMACovariance Matrix Adaptation R^n linear transformationESEvolution Strategynsearch space dimension, i.e., number of decision variablesSymbolsP_GNLLguaranteed no-load loss in Wattsg P_{GLL} guaranteed load loss in Wattsg V_{ks} guaranteed short circuit impedance in percentage λ e_1 IEC standard tolerance for no-load and load loss constraints in % μ e_2 IEC standard tolerance for total loss and impedance $\mu_{cl}^{(2)}$ $voltage constraints in %\mu_{cl}^{(2)}C_{COND}unit cost of ith magnetic material in Euro per kgg_{max}C_{GNL}unit cost of sheet steel in Euro per kgz^{max}C_{OIL}unit cost of mineral oil in Euro per kgz(x)O_{OIL}unit cost of mineral oil in Euro per kgz(x)O_{OIL}unit cost of mineral oil in Euro per kgerr_j(x)C_{OIL}unit cost of mineral oil in E$	NSGA-II	non-dominated sorting genetic algorithm-II	m ^(g)	mean value 'm' of the search distribution at generation g
ESEvolution Strategynsearch space dimension, i.e., number of decision variablesSymbolsPGNLLguaranteed no-load loss in Wattsguaranteed load loss in Wattsguaranteed load loss in Wattsguaranteed load loss in Watts P_{GLL} guaranteed short circuit impedance in percentage λ iteration number V_{ks} guaranteed tolerance for no-load and load loss constraints in % λ number of sampling points e_2 IEC standard tolerance for total loss and impedance μ number of selected best individuals in the population evolution path at generation g e_{2} IEC standard tolerance for total loss and impedance $p_{G}^{(g)}$ conjugate evolution path at generation g $V_{REJ=1,10}$ unit cost of ith magnetic material in Euro per kg g_{max} maximum number of generations C_{GNDD} unit cost of sheet steel in Euro per kg z^{max} objective function value of the worst feasible solution C_{GNL} unit cost of mineral oil in Euro per kg $z(x)$ objective function value of the feasible solution C_{ORL} unit cost of mineral oil in Euro per kg $er_f(x)$ normalized constraint violation	CMA	Covariance Matrix Adaptation	R ⁿ	linear transformation
SymbolsSymbols B_{GNLL} ablesguaranteed no-load loss in Wattsgiteration number P_{GLL} guaranteed load loss in Watts $X_k^{(g+1)}$ U_{ks} guaranteed short circuit impedance in percentage λ e_1 IEC standard tolerance for no-load and load loss con- straints in % μ e_2 IEC standard tolerance for total loss and impedance μ $voltage constraints in %p_{g}^{(g)}conjugate evolution path at generation ge_{2}IEC standard tolerance for total loss and impedancep_{g}^{(g)}voltage constraints in %FFfitness functionC_{FE,i=1,10}unit cost of ith magnetic material in Euro per kgg_{max}C_{SS}unit cost of sheet steel in Euro per kgz^{max}C_{OIL}unit cost of mineral oil in Euro per kgz(x)C_{OIL}unit cost of mineral oil in Euro per kger_f(x)C_{OIL}unit cost of in meral oil in Euro per kger_f(x)$	ES	Evolution Strategy	n	search space dimension, i.e., number of decision vari-
guaranteed no-load loss in Wattsg iteration number P_{GLL} guaranteed load loss in Watts $X_k^{(g+1)}$ U_{ks} guaranteed short circuit impedance in percentage λ e_1 IEC standard tolerance for no-load and load loss con- straints in % μ e_2 IEC standard tolerance for total loss and impedance μ $voltage constraints in %g_{\sigma}^{(g)}conjugate evolution path at generation ge_{1-1,1-10}unit cost of ith magnetic material in Euro per kgg_{max}C_{COND}unit cost of sheet steel in Euro per kgz^{max}C_{ofL}unit cost of mineral oil in Euro per kgz(x)C_{ofL}unit cost of infineral oil in Euro per kgz(x)C_{ofL}unit cost of sheet steel in Euro per kger_f(x)C_{ofL}unit cost of finineral oil in Euro per kger_f(x)C_{ofL}unit $	SymbolsP _{GNLL} ables			
P_{GLL} guaranteed load loss in Watts $X_k^{(B+1)}$ kth offspring from generation $g + 1$; search point U_{ks} guaranteed short circuit impedance in percentage λ number of sampling points e_1 IEC standard tolerance for no-load and load loss con- straints in % μ number of selected best individuals in the population e_2 IEC standard tolerance for total loss and impedance voltage constraints in % μ number of selected best individuals in the population $C_{FE,i=1,10}$ unit cost of ith magnetic material in Euro per kg $p_{g}^{(S)}$ conjugate evolution path at generation g C_{SS} unit cost of sheet steel in Euro per kg max objective function value of the worst feasible solution C_{ofL} unit cost of mineral oil in Euro per kg $z(x)$ objective function value of the feasible solution C_{ofL} unit cost of mineral oil in Euro per kg $er_f(x)$ normalized constraint violation		guaranteed no-load loss in Watts	g	iteration number
U_{ks} guaranteed short circuit impedance in percentage λ number of sampling points e_1 IEC standard tolerance for no-load and load loss con- straints in % μ number of selected best individuals in the population evolution path at generation g e_2 IEC standard tolerance for total loss and impedance voltage constraints in % μ number of selected best individuals in the population gravitic probability $C_{rE,i-1,10}$ unit cost of ith magnetic material in Euro per kg $p_{\sigma}^{(g)}$ conjugate evolution path at generation g C_{cOND} unit cost of conductor in Euro per kg g_{max} maximum number of generations objective function value of the worst feasible solution objective function value of the feasible solution C_{oTL} unit cost of mineral oil in Euro per kg $z(x)$ objective function value of the feasible solution objective function value of the feasible solution	PGLL	guaranteed load loss in Watts	$X_k^{(g+1)}$	kth offspring from generation g + 1; search point
e1 IEC standard tolerance for no-load and load loss con- straints in % μ number of selected best individuals in the population evolution path at generation g e2 IEC standard tolerance for total loss and impedance voltage constraints in % μ number of selected best individuals in the population evolution path at generation g C _{FEJ=110} unit cost of ith magnetic material in Euro per kg gmax z ^{max} Gmax z ^{max} maximum number of generations objective function value of the worst feasible solution objective function value of the feasible solution C _{OTL} unit cost of mineral oil in Euro per kg z(x) objective function value of the feasible solution objective function value of the feasible solution	Uks	guaranteed short circuit impedance in percentage	λ	number of sampling points
straints in % $p_c^{(S)}$ evolution path at generation g e_2 IEC standard tolerance for total loss and impedance voltage constraints in % $p_d^{(S)}$ conjugate evolution path at generation g $C_{FE,I=110}$ unit cost of <i>i</i> th magnetic material in Euro per kg g_{max} fitness function C_{COND} unit cost of conductor in Euro per kg g_{max} objective function value of the worst feasible solution C_{SS} unit cost of sheet steel in Euro per kg $Z(x)$ objective function value of the feasible solution C_{OIL} unit cost of mineral oil in Euro per kg $er_f(x)$ normalized constraint violation	e1	IEC standard tolerance for no-load and load loss con-	μ_{\perp}	number of selected best individuals in the population
e_2 IEC standard tolerance for total loss and impedance voltage constraints in % $p_{\sigma}^{(g)}$ conjugate evolution path at generation g fitness function $C_{FE,I=110}$ unit cost of <i>i</i> th magnetic material in Euro per kg FF fitness function maximum number of generations objective function value of the worst feasible solution objective function value of the feasible solution C_{OND} unit cost of sheet steel in Euro per kg Z^{max} C_{ONL} unit cost of mineral oil in Euro per kg $Z(x)$ C_{OIL} unit cost of mineral oil in Euro per kg $er_f(x)$ C_{OIL} unit cost of in mineral oil in Euro per kg $er_f(x)$		straints in %	$p_{c}^{(g)}$	evolution path at generation g
voltage constraints in %FFfitness function $C_{FE,i=1,10}$ unit cost of ith magnetic material in Euro per kg g_{max} maximum number of generations C_{COND} unit cost of conductor in Euro per kg z^{max} objective function value of the worst feasible solution C_{SS} unit cost of sheet steel in Euro per kg $z(x)$ objective function value of the feasible solution C_{OIL} unit cost of mineral oil in Euro per kg $en_j(x)$ normalized constraint violation	e ₂	IEC standard tolerance for total loss and impedance	$p_{\sigma}^{(g)}$	conjugate evolution path at generation g
$C_{FE,I=1,10}$ unit cost of ith magnetic material in Euro per kg g_{max} maximum number of generations C_{COND} unit cost of conductor in Euro per kg z^{max} objective function value of the worst feasible solution C_{SS} unit cost of sheet steel in Euro per kg $z(x)$ objective function value of the feasible solution C_{OIL} unit cost of mineral oil in Euro per kg $en_j(x)$ normalized constraint violation		voltage constraints in %	FF	fitness function
C_{COND} unit cost of conductor in Euro per kg z^{max} objective function value of the worst feasible solution C_{SS} unit cost of sheet steel in Euro per kg $z(x)$ objective function value of the feasible solution C_{OIL} unit cost of mineral oil in Euro per kg $en_j(x)$ normalized constraint violation	$C_{FE,i=1,10}$	unit cost of ith magnetic material in Euro per kg	gmax	maximum number of generations
C_{SS} unit cost of sheet steel in Euro per kg $z(x)$ objective function value of the feasible solution C_{OIL} unit cost of mineral oil in Euro per kg $e\pi_j(x)$ normalized constraint violation	CCOND	unit cost of conductor in Euro per kg	Zmax	objective function value of the worst feasible solution
$C_{OII.}$ unit cost of mineral oil in Euro per kg $e\pi_j(x)$ normalized constraint violation	C.55	unit cost of sheet steel in Euro per kg	Z(X)	objective function value of the feasible solution
Country Figure 1 and a Figure 1 and	Con	unit cost of mineral oil in Euro per kg	$em_j(x)$	normalized constraint violation
CINS Unit cost of insulating paper in Euro per kg Peval Maximum number of function evaluations	CINS	unit cost of insulating paper in Euro per kg	Feval	Maximum number of function evaluations
C _{DS} unit cost of duct strips in Euro per kg H Hessian matrix	CDS	unit cost of duct strips in Euro per kg	Н	Hessian matrix
C _{CORR} unit cost of corrugated panel in Euro per kg P _t parent population of MOP	CCORR	unit cost of corrugated panel in Euro per kg	P_t	parent population of MOP
$x_{t=1,2,n}$ th design variable Q_t offspring population of MOP	Nt=1,2.n	tth design variable	Qt	offspring population of MOP
$z_{p=1,,4}$ pth objective function R_t combined population of MOP	Zp=1,,4	pth objective function	Rt	combined population of MOP
$h_{j=1,2,q}$ Jth inequality constraint $f_{i=1,-M}$ 'M' objective function values of MOP	hj=1,2_q	jth inequality constraint	Ji=1,M	'M' objective function values of MOP
G _{FE,i=1,10} weight of ith magnetic material in kg 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, nonlinear, 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 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' 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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