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Power Transformer Design Resorting to Metaheuristics Techniques

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Abstract. Power transformers have a key role in the power system grids. Their manufacturing and design must consider several aspects, such as technical limits, legal constraints, security constraints and manufacturing price. Considering only power transformers' active parts, it is possible to identify 20 manufacturing specific parameters, and in economic point of view, 13 variables are also considered. Using a classic approach, variables are chosen accordingly with the defined constraints, followed by a sensitivity analysis performed to each variable, to optimize the manufacturing cost. This procedure can be time consuming and the optimum may not be reached. In this paper, genetic algorithms are used. An innovative approach through the introduction of genetic compensation concept in mutation operator is detailed. Results pointed out an increased performance and consistency when compared with the classical approach.

Keywords: Power Transformer, Genetic Algorithms, Genetic Compensation.

1 Introduction

Power transformers design is a challenging task requiring simultaneously an agreement between imposed constraints, such as standards and specifications, and keeping manufacturing cost as low as possible. Several design improvements were made to increase power transformer efficiency and decrease manufacturing cost. One example was replacing conventional steel by amorphous laminated steel, resulting in no load losses reduction, about 70% [1]. According to [2], four power transformer designing methodologies can be considered: i) Experimental methods – where binding analytical methods with experimental measurements, results in a precise mathematical model; ii) Equivalent electric circuit – this modeling technique results into a semi-empirical model, but outcomes are satisfactory and this method still be used in industry; iii) Numerical methods – a common tool used to study and model power transformers, being finite elements methods usually applied; iv) Stochastic

methods - including artificial intelligence (AI) methods, such as particle swarm optimization (PSO), artificial neural networks (ANN), ant colony optimization (ACO) or genetic algorithms (GA), are rising up.

In literature and among other AI methods, PSO is used for power transformers winding modelling in [3]. ACO technique is used in [4] for power transformer nominal power design and for total cost minimization in [5]. NN are used in [6] for no load losses reduction, for magnetization current minimization in [7], to support winding material selection in [8] or to minimize manufacturing cost in [9]. GA, on their turn are used in [10] to minimize leakage magnetic field, in [11], to minimize both losses and manufacturing costs, in [12] for total cost minimization, or in [13] to minimize only the manufacturing cost.

In this paper, GA is used to minimize power transformer manufacturing cost and an innovative parameter, named as genetic compensation (GC) is included into mutation operator. This paper is organized as follows: in section 2 a relationship to applied AI systems is addressed. In section 3, the GA used is described and the GC parameter developed is detailed. In section 4, the developed methodology is analyzed and in section 5 conclusions are pointed out.

2 Relationship to Applied Artificial Intelligence Systems

In power transformer design is possible to apply traditional methods as the ones described in i-iii (section 1). However, state-of-the art tools based on AI techniques are being used and are revealing new approaches which are less time consuming and allowing available resources optimization. For power transformer design, and if only transformer' active parts are considered, 20 construction parameters must be taken into account. Some of them are detailed in table 1.

Table 1. Intrinsic power transformer parameters examples for 630kVA, 20/0.4kV.

Variable	Value	Description
BIL_{HV-LV}	$150e^{-3}; 10e^3[V]$	Basis insulation for high voltage and low voltage
g_{HV-LV}	$8856 [kgm^{-3}]$	High voltage (HV), low voltage (LV) specific mass
$LDSP_{HV-LV}$	1; 0.909	HV and LV winding spatial direction factor
$T_{o,max}$	100 [°C]	Oil maximum temperature
$T_{w,max}$	100 [°C]	Winding maximum temperature
$Induced_{max}$	$6e^3 [V]$	Maximum induced voltage for 0.28mm insulation
P_{HV-LV}	$2.0968e^{-8} [\Omega m]$	LV and LV winding resistivity

In addition, and considering the economic point of view, 13 parameters must be considered, where some of them are shown in table 2. So, this is a complex multidimensional problem that is subjected to a large amount of constraints. The

traditional approach described in [14] was implemented and used as comparison basis with the GA developed method. This traditional and semi empirical method implementation was useful, not only to contextualize the design approach using AI, but also to understand the system variables and their corresponding outcomes.

There are several AI techniques used in power transformer design, as the ones [1-13] mentioned in section 1. All of them have a couple of important features in common, which are the improvement of methods efficiency and optimization. Here, the optimization can be economic, by means of cost reduction resulting in manufacturing energy savings or by using more suitable materials avoiding unnecessary losses (economic or even electrical losses). This paper contribution to applied intelligence systems field, is in line with the previously referred literature, however, an additional and important contribution is given in what concerns to the GA performance, as detailed in section 3.

Table 2. Economic power transformer parameters examples.

Variable	Units	Description
A	[\$W ⁻¹]	No load losses cost
B	[\$W ⁻¹]	Load losses cost
uc _{1,2}	[\$kg ⁻¹]	High voltage and low voltage winding costs
uc ₆	[\$kg ⁻¹]	Mineral oil cost
C _{lab}	[\$]	Labor cost

3 Power Transformer Design Model

To apply the GA on the power transformer design is mandatory to define the model parameters. Those parameters are given by the chromosomes alleles as described in table 3.

Table 3. Chromosome alleles considered in GA definition.

Allele	Variable (x_i)	Description
1	Turns_LV	Low voltage winding turns
2	D	Core width
3	FD	Magnetic induction
4	G	Core window' height
5	t_LV	Low voltage conductive tape thickness
6	d_HV	High voltage conducting wire diameter

The fitness function shown in equation (1) aggregates all the calculus defined in [14] and receive as inputs the parameters shown in table 3.

$$[CTM, TOC, dvar] = f(x_i) \quad (1)$$

In (1) the fitness function depends on CTM parameter, which is the power transformer manufacturing cost; Also, it's possible to consider other parameter, defined as TOC, which is the power transformer total ownership cost. The output parameter, defined as *dvar* is the variables set which are subjected to the constraints shown in table 4. Costs are obtained by following the dimensioning equations presented in [14] and are subdivided in materials (LV/HV winding, magnetic material, insulation, duct strips, etc.), manufacturing and sales margin.

Table 4. Constrained variables.

Constraint	Variable (x_i)	Description
1	$dvar_1$	Induced voltage (equal constraint)
2	$dvar_2$	Turns ratio (equal constraint)
3	NLL	No load losses
4 & 5	LL_LV; LL_HV	Load losses for low and high voltage
6 & 7	TL_LV; TL_HV	Total losses for low and high voltage
8	TLRRT	Heat transfer
9	U_k	Short-circuit impedance
10	AOR	Heat increasing
11 & 12	Induced_LV,HV	Induced voltage on low and high voltage windings
13 & 14	Impulse_LV,HV	Voltage impulse on low and high voltage windings
15	TH_min	Tank height

3.1 GA Operator's Characterization

In this section the GA operators, namely selection, crossover, mutation, elitism and stopping criteria are characterized. Selection can be made using: i) proportional method; ii) ranking selection; iii) tournament selection and iv) stationary selection [15]. Considering the power transformer design case study, it is important to guarantee that selection method can include constraints. Despite being possible to use penalties in the decision variable in both, ranking selection and proportional method, this is a complex implementation process because it implies an exhaustive analysis of all decision variables. To obviate this difficulty, the tournament selection is pointed out by [16] as a solution that enables comparing individuals, relating them with the decision variable and also allowing to make this comparison taking into account the accomplishment of the defined constraints. So, in this case study, a binary tournament selection with constraints, based on [16] is performed.

Crossover operator allows to produce offspring, i.e., allows to produce a set of new possible solutions for the problem. The common crossover types are single point, multipoint and uniform. Because no major differences were noticed by using different crossover types, in this case study single point crossover is performed.

Mutation operator allows to change randomly an allele position, changing the chromosome genetics and is used to ensure the searching for a solution in the overall variables' domain. In [17] is demonstrated that a mutation coefficient higher value can be need for complex problems, as the one considered in this case study. However, the mutation effect can result in new individuals less fit, being this setback solved by natural selection that will eliminate these individuals in future generations. Last studies, showed that in nature, has been observed that mutation tends to be softened, decreasing the pure random mutation characteristic. This phenomenon is defined as GC [18] and will be modeled and implemented as detailed in section 3.2.

Elitism guarantees that the most fit individuals of a previous generation are copied and inserted in the next generation, resulting in a better and quicker algorithm convergence [19]. When a problem with constraints is considered, the elitism operator needs to be adapted, assuring that only parents that satisfy the constraints are chosen and only replace the offspring that don't satisfy the constraints or have worst fitness value than the parents. In this case study 2 stopping criteria were used. The generation limit empirically defined as one hundred times bigger than variables number, and stall. If the GA is still running without an improvement of the fitted individual, then the stall stopping criteria acts.

3.2 Mutation with Genetic Compensation Effect

For a more effective mutation based on nature genetic compensation, the following procedure is applied: when a viable solution occurs, the mutation domain is limited by a range defined around the fitness value of the better fitted individual. For example, assuming a variable domain between 0 and 100 that accomplish the imposed constraints and that for a time instant the most fitted individual for that variable is 15, for that time ahead the mutation will be only possible for a range around 15. If a compensation rate of 10% is chosen, then mutation occurs between 13 and 17 instead between 0 and 100. The proposed approach may slightly increase the risk of falling into a local minimum. The mathematical formulation of this mutation with GC effect is given by (3).

$$x_i^{mutant} = x_i^{best} \times [1 + C_{gencomp} \times (2RAND - 1)] \quad (3)$$

Where x_i^{mutant} is the new i allele value, x_i^{best} is the best i allele value, $C_{gencomp}$ is the GC effect rate and $RAND$ is a random value between 0 and 1.

3.3 GA Parameters Definition

In this case study a 200 population size is considered and was defined by GA performance analysis, through tests with 10, 20, 50, 100, 200, 500 and 1000 individuals, which results are shown in Fig. 1.

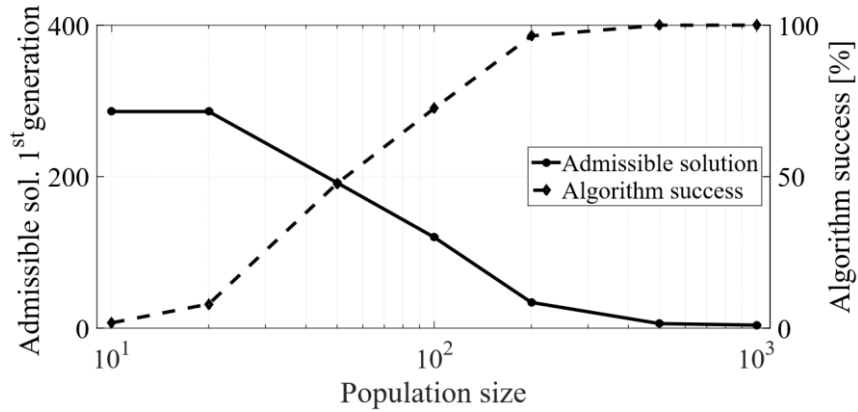


Fig. 1. Population size definition based on admissible solution and algorithm success.

The considered crossover coefficient is 1 (100%) and was also defined by GA performance analysis, through tests shown in Fig.2, considering 0.01, 0.08, 0.4, 0.8 and 1 crossover coefficient values. Elitism coefficient was considered 5%, the stall stopping criteria was defined at 50 generations and every set of parameters was tested 43 times. The best combination of mutation and GC was found to be 50% and 5%, respectively, as shown in Fig. 3. The corresponding processing time is shown in Fig. 4.

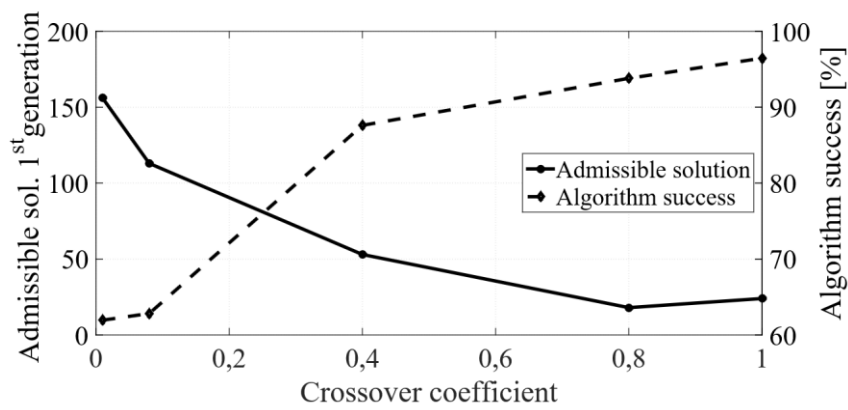


Fig. 2. Crossover coefficient definition based on admissible solution and algorithm success.

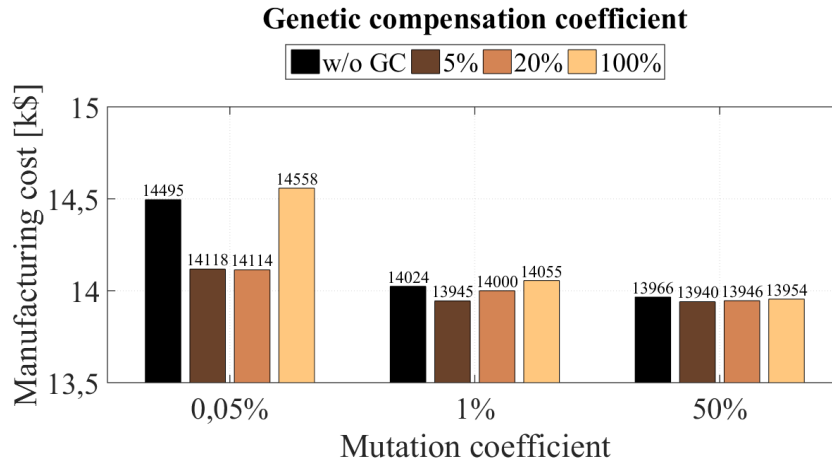


Fig. 3. Mutation coefficient with genetic compensation effect on manufacturing cost.

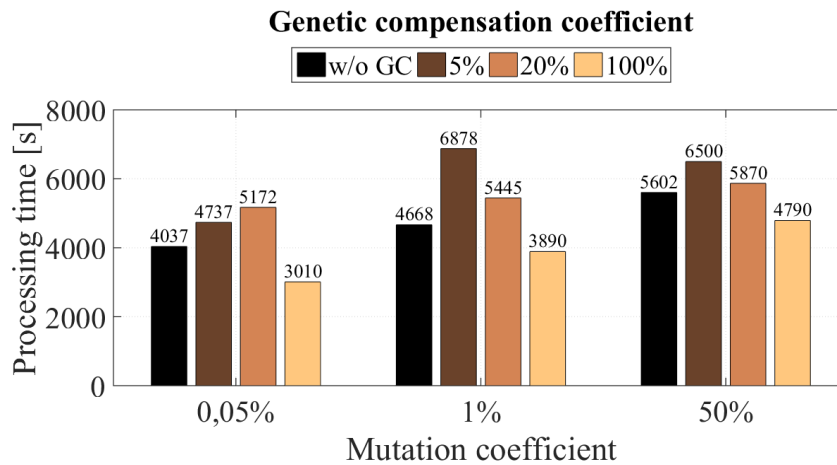


Fig. 4. Mutation coefficient with genetic compensation effect on processing time.

4 Case Study Analysis

Using the traditional power transformer design described in [14] the manufacturing cost is optimized through a sensibility analysis performed by brute-force (BF), consisting in thorough search of the best solution among all admissible solutions, that

satisfy the manufacturing requirements and resulting in a benchmark definition. The obtained results are shown in table 5.

Table 5. Best results obtained with brute-force.

Iteration	Manufacturing Cost [\$]	Processing time [s]
1	14 672	114
2	14 275	236
3	14 026	47
4	13 945	149

As observed in both Fig.3 and Fig.4, GA with GC effect contributes for a manufacturing cost decreasing but the processing time is always superior than the values observed in table 5. Using the GA with GC effect it is possible to obtain a manufacturing cost of \$13 940, inferior to the manufacturing costs registered in table 5 and inferior to all values shown in Fig. 3. Nevertheless, the processing time was 43.6 times bigger when compared with the 4th iteration shown in table 5, with 6500s of processing time used. Despite this increased processing time, there are benefits in running the algorithm without defining feasible starting values. Starting with random solutions, GA can achieve optimal or quasi-optimal solutions. These tools can show good performances in problems without obvious first feasible solutions.

5 Conclusions

Traditional power transformer design is a method that show good results, however the use of new techniques based on AI are taking place and evolving. This paper shows a contribution by using GA with GC effect. The study was performed by comparison with the BF, using 4 iterations. For the GA operator's definition several performance tests were made, regarding the minimization of the power transformer manufacturing cost, but also considering GA success and processing time. It is possible to conclude, that GA improved the attainment of a better solution, reaching a lower manufacturing cost when compared with BF result. As values of some parameters got smaller and reaching construction tolerances, no further steps were taken in BF. The best result obtained with BF is near to the one obtained with GA. It is also possible to conclude that processing time using GA exceeds the one needed by the BF. However, GA starts performing a blind search without predefined known values as happens with the semi empirical methods, being an adequate exploratory tool to study new transformers models. When traditional methods are used, several iterations must be performed to obtain improved results, so the overall time process should be also considered. The introduction of the GC showed promising results increasing the search capacity.

These values can be improved with future research regarding GC coefficient. For

future developments, results comparison with other AI techniques, such as PSO or ACO will be addressed.

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