Proceedings of the 8th World Congress on Mechanical, Chemical, and Material Engineering (MCM'22)
Prague, Czech Republic – July 31, 2022 - August 02, 2022
Paper No. ICMIE 102
DOI: 10.11159/icmie22.102

Design Optimization of 10 kW High Speed Generator by using Salp Swarm Algorithm

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Abstract **-** The design of a 10 kW high-speed generator is optimized in this research. The objective is to optimize the design parameters of the high speed generator namely pole body width, pole shoe height, pole shoe width for the responses (pole shoe flux density, pole body flux density, rotor yoke flux density, efficiency, shaft torque, exciting current, exciting current density). Response surface face centered design is used for experimental design and mathematical modelling. Then salp swarm algorithm – which is a recently invented meta-heuristic algorithm – is used for performing the optimization. The experimental data is obtained from ANSYS MAXWELL simulations. The confirmations are also performed by ANSYS MAXWELL. The results show that the SSA is a good optimizer for these types of electric machines.

Keywords**:** high speed generator, salp swarm algorithm, design optimization.

1. Introduction

Many researchers have studied magnetic device design optimization over the last few decades. However there are limited studies published on optimizing the design of high speed generators. Sadeghierad et al. [1] studied on optimizing the design of a high speed axial flux generator (HSAFG). To improve the efficiency of the HSAFG, particle swarm optimization (PSO) and genetic algorithm (GA) are used. The effect of the lambda (ratio of inner diameter / outer diameter) is discussed. Ismagilov et al. [2] performed experimental trials on the new topology of the stator magnetic core made from amorphous alloy for 5 kW 60000 rpm high speed permanent magnet electric machine with a tooth-coil winding with 6 slots and 2 and 4 poles. Guo et al. [3] used gradient descent based optimization to minimize the volume of high speed generator for micro turbojet engine. They proposed an improved electromagnetic parameter calculation method that computed the back electromotive force using air gap static flux density distribution and calculating the coil average inductance at quadrature-direct axis midline. The studies about design optimization of high speed generator by the aid of meta-heuristics are very limited. In this study design optimization of 10 kW high speed generator by the aid of salp swarm algorithm (SSA) is performed. Design parameters of the high speed alternator that will be optimized are presented in Figure 1.

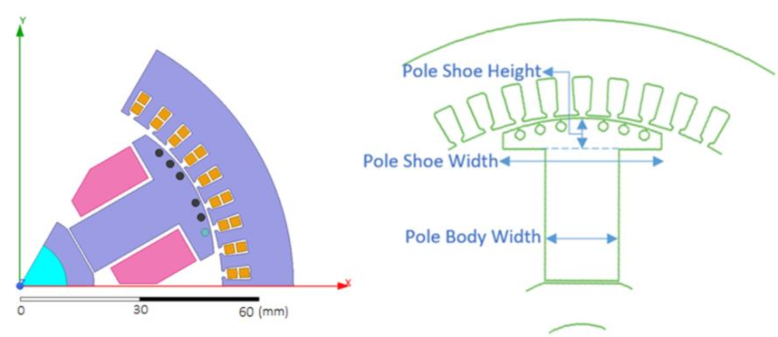

Fig.1: Design parameters of the10 kW high speed alternator that will be optimized.

The responses (performance criteria) are selected as the pole shoe flux density, pole body flux density, rotor yoke flux density, efficiency, shaft torque, exciting current, exciting current density. The factors those will be optimized are the pole body width (PBW), pole shoe height (PSH), pole shoe width (PSW). The effect of the PBW, PSH, and PSW on the selected responses has not been studied together previously and this is the first novelty of this study. Another novelty aspect of this study is the optimization method that is used. Salp swarm algorithm is not previously used for design optimization of high speed generators. Next section describes the details of the SSA. The experimental results and the conclusions are presented in Section 3 and 4, respectively.

2. Salp Swarm Algorithm

Meta-heuristics are the stochastic optimization techniques and they do not need calculating the derivative of the search space. This property makes them highly flexible. Also meta-heuristics use random operators and this enables them from avoiding local solutions [4-6]. The SSA – which is invented in 2017 by Mirjalili et al – is a meta-heuristic algorithm. SSA is based on salps' swarming behavior in the oceans (navigating and foraging). Salps are members of the Salpidae family and have a translucent barrel-shaped body. Salps frequently form a swarm known as a salp chain in deep waters. The primary motivation for this activity is to improve mobility through quick synchronized alterations and foraging [6]. The population is split into two groups: leaders and followers in order to mathematically simulate the salp chains. The salp on the front of the chain is the leader and the remaining salp followers. Salps' location is defined in an n-dimensional search space, where n is the number of variables in a particular problem and all salp positions are recorded in a 2D matrix named x. The pseudo code for multi-objective SSA is given in Fig. 2 [6].

Initialize the salp population x_i (where i=1, 2,…,n)
While (*end condition is not met*)
  Calculate the fitness of each search agent (salp)
  Determine the non-dominated salps
  Update the repository (*by considering the obtained non-dominated salps*)
  If the repository becomes full
    Call the repository maintenance procedure to remove one repository resident
    Add the non-dominated salp to the repository
  End
  Choose a source of food from repository: F=*SelectFood(repository)*
  Update c_1 by $c_1 = 2e^{-\left(\frac{4l}{L}\right)^2}$
  For each salp (x_i)
    If i=1
      Update the position of the leading salp:

$$x_j^1 = \begin{cases} F_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 \geq 0 \\ F_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 < 0 \end{cases}$$

    Else
      Update the position of the follower salp:

$$x_j^i = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right)$$

    End
  End
  Amend the salps based on the *ub* and *lb*
End
Return repository

Fig. 2: Pseudo code for multi-objective SSA.

In this pseudocode, x_j^1 and F_j shows the position of the leader salp (first salp) and the food source's position (optimized values for the responses) in the *j*th dimension, respectively. The first salp adjusts its position in relation to the food source. lb_j and the ub_j are the lower and upper bounds of the *j*th dimension, while c_1, c_2, and $c_3$are the random numbers. c_2 and c_3 are the random numbers between [0, 1], However, c_1 strikes a balance between exploration and exploitation. L and l are the maximum number of iterations and the current iteration, respectively. x_j^i is the ith follower's position. The positions of the salps indicate the optimum factor levels. By using the pseudocode given in Fig. 2, over the course of iterations, the leader salp shifts its position around the food source, and the follower salps progressively follow it. The distribution of points searched around the start point is higher than the distribution of points searched around the finish point. This is related to the c_1 parameter, which affects both mobile and stationary food source exploration and exploitation [6].

3. Experimental Results

The goal of this study is to determine the best design values for PBW (X_1), PSH (X_2), and PSW (X_3) to obtain the desired response values (namely pole shoe flux density (Y_1), pole body flux density (Y_2), rotor yoke flux density (Y_3), efficiency (Y_4), shaft torque (Y_5), exciting current (Y_6), exciting current density (Y_7)) for the 10 kW high speed generator. The dimensions of the factors are given in millimetres (mm). The objective is to obtain target magnetic flux density values for pole shoe flux density (min: 0.9 Tesla, target:1 Tesla, max:1.2 Tesla), pole body flux density (min: 1.3 Tesla, target:1.5 Tesla, max:1.7 Tesla), and rotor yoke flux density (min: 0.4 Tesla, target:0.5 Tesla, max:0.6 Tesla). The other targets for the remaining responses are obtaining the maximum efficiency, and minimizing the shaft torque, exciting current, exciting current density.

The experiment is designed using response surface face centered design, a well-known design of experiment technique [7, 8]. The factor levels are determined (as [min, max] values) as [9, 17], [6, 10], and [30, 40] for the PBW, PSH, and PSW; respectively. The corresponding center points are 13, 8, and 35. Table 1 shows the experimental design.To perform multi-objective optimization by using SSA (or any other metaheuristics) the factor levels have to be transformed to coded factor levels between -1 and +1 to ensure that factors are unit-independent and unified under a single objective function. The coding is performed by using Eq. (1):

$$\mathrm{X_{coded}} = \frac{\mathrm{X_{uncoded}} - \left((\mathrm{X_{max}} + \mathrm{X_{min}})/2\right)}{(\mathrm{X_{max}} - \mathrm{X_{min}})/2} \tag{1}$$

Table 1: ANSYS MAXWELL Simulation results for the experimental design.

	Factors (Uncoded)			Factors (Coded)			Responses						
Run	X_1 (mm)	X_2 (mm)	X_3 (mm)	X_1 (mm)	X_2 (mm)	X_3 (mm)	Y_1 (Tesla)	Y_2 (Tesla)	Y_3 (Tesla)	Y_4 (%)	Y_5 (N.m)	Y_6 (A)	Y_7 (A/mm^2)
1	9	6	30	-1	-1	-1	0.98	2.10	0.45	81.82	10.21	53.28	8.57
2	17	6	30	1	-1	-1	0.98	1.11	0.43	89.56	9.32	23.37	5.64
3	9	6	40	-1	-1	1	0.69	2.25	0.48	79.97	10.44	58.20	9.37
4	17	6	40	1	-1	1	0.69	1.19	0.46	89.52	9.33	23.65	5.71
5	9	10	30	-1	1	-1	1.01	2.16	0.57	77.65	10.76	55.82	11.98
6	17	10	30	1	1	-1	1.01	1.14	0.53	87.45	9.55	23.73	9.17
7	9	10	40	-1	1	1	0.72	2.34	0.62	74.35	11.23	62.87	13.49
8	17	10	40	1	1	1	0.72	1.24	0.57	87.21	9.58	24.33	9.40
9	9	8	35	-1	0	0	0.81	2.20	0.52	78.35	10.66	57.12	11.03
10	17	8	35	1	0	0	0.82	1.17	0.49	88.42	9.44	23.64	7.61
11	13	8	30	0	0	-1	0.99	1.48	0.49	88.05	9.48	28.25	6.82
12	13	8	40	0	0	1	0.70	1.58	0.53	87.45	9.55	30.06	7.26
13	13	6	35	0	-1	0	0.80	1.51	0.46	89.02	9.38	28.40	5.48
14	13	10	35	0	1	0	0.83	1.55	0.57	86.93	9.61	29.62	8.17
15	13	8	35	0	0	0	0.82	1.53	0.51	87.86	9.50	28.97	6.99

MINITAB statistical software is used to calculate the mathematical models that represent the relationships between the responses and the factors. The original models which are calculated from the uncoded (original) factor levels are given in Eqs. (2) - (8) below. These models are needed to show the real relationship to the readers. However, to perform the optimization, the coded factor levels are used in the modelling phase to convert the responses being independent from the units. In order to use the SSA, the factors must be coded between -1 and 1. By this way, the multi-objective optimization can be performed by combining all the response models under unique goal function. The mathematical models - which will be used in optimization phase - calculated by using coded factor levels are presented in Eqs. (9) - (15).

$$Y_1 \text{ (Pole Shoe Flux Density)} = 3.36235416666666 - 0.00245833333333346\mathrm{X}_1 + 0.00083333333333339\mathrm{X}_2 - 0.117666666666666\mathrm{X}_3 + 0.000104166666666667X_1^2 + 0.000416666666666676X_2^2 + 0.00126666666666666X_3^2 - 0.00000000000000002\mathrm{X}_1\mathrm{X}_2 + 0.00000000000000001\mathrm{X}_1\mathrm{X}_3 - 0.00000000000000005\mathrm{X}_2\mathrm{X}_3 \quad (2)$$

$$Y_2 \text{ (Pole Body Flux Density)} = 4.1645486111111 - 0.344826388888889\mathrm{X}_1 - 0.00526736111111054\mathrm{X}_2 + 0.0116097222222225\mathrm{X}_3 + 0.00986111111111111X_1^2 + 0.000694444444444447X_2^2 + 0.000111111111111107X_3^2 - 0.00109375000000004\mathrm{X}_1\mathrm{X}_2 - 0.000937499999999998\mathrm{X}_1\mathrm{X}_3 + 0.000624999999999995\mathrm{X}_2\mathrm{X}_3 \quad (3)$$

$$Y_3 \text{ (Rotor Yoke Flux Density)} = 0.344104166666666 + 0.00985416666666667\mathrm{X}_1 - 0.000635416666666592\mathrm{X}_2 - 0.00305416666666666\mathrm{X}_3 - 0.000208333333333333X_1^2 + 0.0016666666667X_2^2 + 0.0000666666666666668X_3^2 - 0.000781249999999999\mathrm{X}_1\mathrm{X}_2 - 0.0000625\mathrm{X}_1\mathrm{X}_3 + 0.000374999999999999\mathrm{X}_2\mathrm{X}_3 \quad (4)$$

$$Y_4 \text{ (Efficiency)} = 50.0305486111112 + 6.74879861111111\mathrm{X}_1 - 1.73501736111111\mathrm{X}_2 - 0.10706527777778\mathrm{X}_3 - 0.278263888888889X_1^2 + 0.0344444444444444X_2^2 - 0.00348888888888882X_3^2 + 0.0839062500000007\mathrm{X}_1\mathrm{X}_2 + 0.0304374999999999\mathrm{X}_1\mathrm{X}_3 - 0.0206250000000002\mathrm{X}_2\mathrm{X}_3 \quad (5)$$

$$Y_5 \text{ (Shaft Torque)} = 13.9397916666667 - 0.788458333333332\mathrm{X}_1 + 0.196770833333334\mathrm{X}_2 + 0.0111583333333333\mathrm{X}_3 + 0.0341666666666667X_1^2 - 0.00208333333333332X_2^2 + 0.000466666666666667X_3^2 - 0.0134375000000001\mathrm{X}_1\mathrm{X}_2 - 0.004125\mathrm{X}_1\mathrm{X}_3 + 0.00325000000000001\mathrm{X}_2\mathrm{X}_3 \quad (6)$$

$$Y_6 \text{ (Exciting Current)} = 168.642861111111 - 19.5953263888889\mathrm{X}_1 + 0.403795138888912\mathrm{X}_2 + 0.367484722222235\mathrm{X}_3 + 0.714548611111111X_1^2 + 0.015694444444445X_2^2 + 0.00831111111111092X_3^2 - 0.0964062500000023\mathrm{X}_1\mathrm{X}_2 - 0.0693125\mathrm{X}_1\mathrm{X}_3 + 0.0306249999999999\mathrm{X}_2\mathrm{X}_3 \quad (7)$$

$$Y_7 \text{ (Exciting Current Density)} = 23.333111111111 - 3.70257638888888\mathrm{X}_1 + 1.28323263888889\mathrm{X}_2 + 0.0455347222222235\mathrm{X}_3 + 0.144548611111111X_1^2 - 0.0455555555555555X_2^2 + 0.00131111111111109X_3^2 - 0.00484375000000049\mathrm{X}_1\mathrm{X}_2 - 0.0125625\mathrm{X}_1\mathrm{X}_3 + 0.010875\mathrm{X}_2\mathrm{X}_3 \quad (8)$$

Table 2 displays the statistical analysis results obtained from MINITAB. According to these findings, the R^2 values are very high (nearly 100 percent), indicating that these three factors are sufficient to explain the responses. Also, the P-values are less than 5%, indicating that these models are significant and can be used for optimization.

Table 2: Results of statistical analysis for mathematical models.

Response	R^2 (Coefficient of Determination) Results			ANOVA Results	
	R^2 (%)	R^2 (Prediction) (%)	R^2 (Adjusted) (%)	P-Value	Result
Y_1	99.96	99.77	99.90	0.000<0.05	Significant
Y_2	99.98	99.84	99.95	0.000<0.05	Significant
Y_3	99.89	98.62	99.71	0.000<0.05	Significant
Y_4	99.64	95.92	98.99	0.000<0.05	Significant
Y_5	99.41	93.02	98.35	0.000<0.05	Significant
Y_6	99.95	99.41	99.87	0.000<0.05	Significant
Y_7	99.42	94.06	98.37	0.000<0.05	Significant

The prediction performances of the models are shown in Table 3. In Table 3, Y_i values represents the observed values (ANSYS MAXWELL simulation results), and the $\hat{Y}_i$ are the expected values (fitted values using MINITAB to the mathematical models). PE is the prediction error ($PE_i(\%) = \left(\left|Y_i - \hat{Y}_i\right|/\hat{Y}_i\right)100$):

Table 3: Prediction performances.

Run (i)	Pole Shoe Flux Density (Tesla)			Pole Body Flux Density (Tesla)			Rotor Yoke Flux Density (Tesla)			Efficiency (%)		
	Y_{i1}	$\hat{Y}_{i1}$	PE_{i1} (%)	Y_{i2}	$\hat{Y}_{i2}$	PE_{i2} (%)	Y_{i3}	$\hat{Y}_{i3}$	PE_{i3} (%)	Y_{i4}	$\hat{Y}_{i4}$	PE_{i4} (%)
1	0.98	0.9787	0.14	2.10	2.1019	0.09	0.45	0.4489	0.24	81.82	81.7449	0.09
2	0.98	0.9807	0.07	1.11	1.1169	0.61	0.43	0.4319	0.44	89.56	89.1889	0.42
3	0.69	0.6887	0.19	2.25	2.2489	0.05	0.48	0.4819	0.40	79.97	79.7339	0.30
4	0.69	0.6907	0.10	1.19	1.1889	0.10	0.46	0.4599	0.02	89.52	89.6129	0.10
5	1.01	1.0087	0.13	2.16	2.1609	0.04	0.57	0.5699	0.01	77.65	77.5549	0.12
6	1.01	1.0107	0.07	1.14	1.1409	0.08	0.53	0.5279	0.39	87.45	87.6839	0.27
7	0.72	0.7187	0.19	2.34	2.3329	0.31	0.62	0.6179	0.34	74.35	74.7189	0.49
8	0.72	0.7207	0.09	1.24	1.2379	0.17	0.57	0.5709	0.16	87.21	87.2829	0.08
9	0.81	0.8153	0.65	2.20	2.2056	0.25	0.52	0.5213	0.26	78.35	78.3876	0.05
10	0.82	0.8173	0.33	1.17	1.1656	0.38	0.49	0.4893	0.14	88.42	88.3916	0.03
11	0.99	0.9913	0.13	1.48	1.4696	0.71	0.49	0.4913	0.27	88.05	88.3576	0.35
12	0.70	0.7013	0.19	1.58	1.5916	0.73	0.53	0.5293	0.13	87.45	87.1516	0.34
13	0.80	0.8013	0.17	1.51	1.5036	0.43	0.46	0.4573	0.58	89.02	89.6096	0.66
14	0.83	0.8313	0.16	1.55	1.5576	0.49	0.57	0.5733	0.58	86.93	86.3496	0.67
15	0.82	0.8147	0.65	1.53	1.5278	0.15	0.51	0.5087	0.26	87.86	87.8418	0.02

Table 3: Continues.

Run (i)	Shaft Torque (N.m)			Exciting Current (A)			Exciting Current Density (A/mm^2)		
	Y_{i5}	$\hat{Y}_{i5}$	PE_{i5} (%)	Y_{i6}	$\hat{Y}_{i6}$	PE_{i6} (%)	Y_{i7}	$\hat{Y}_{i7}$	PE_{i7} (%)
1	10.21	10.2172	0.07	53.28	53.2479	0.06	8.57	8.6279	0.67
2	9.32	9.3812	0.65	23.37	23.8489	2.01	5.64	5.8259	3.19
3	10.44	10.4792	0.37	58.2	58.3399	0.24	9.37	9.5229	1.61
4	9.33	9.3132	0.18	23.65	23.3959	1.09	5.71	5.7159	0.10
5	10.76	10.7772	0.16	55.82	56.0719	0.45	11.98	11.9759	0.03
6	9.55	9.5112	0.41	23.73	23.5879	0.60	9.17	9.0189	1.68

7	11.23	11.1692	0.54	62.87	62.3889	0.77	13.49	13.3059	1.38
8	9.58	9.5732	0.07	24.33	24.3599	0.12	9.4	9.3439	0.60
9	10.66	10.6573	0.03	57.12	57.2416	0.21	11.03	11.0076	0.20
10	9.44	9.4413	0.01	23.64	23.5276	0.48	7.61	7.6256	0.20
11	9.48	9.4333	0.49	28.25	27.6936	2.01	6.82	6.7316	1.31
12	9.55	9.5953	0.47	30.06	30.6256	1.85	7.26	7.3416	1.11
13	9.38	9.2893	0.98	28.4	28.0676	1.18	5.48	5.0776	7.93
14	9.61	9.6993	0.92	29.62	29.9616	1.14	8.17	8.5656	4.62
15	9.5	9.5027	0.03	28.97	28.9518	0.06	6.99	7.0038	0.20

The results in Table 3 indicate that the mathematical models good-fit the observations. As mentioned before, to perform optimization using MATLAB the mathematical models calculated from coded factor levels are used. The mathematical models for the coded factor levels are also calculated by using MINITAB, and are presented in Eqs. (9) - (15).

$$Y_{1,coded} \text{ (Pole Shoe Flux Density)} = 0.814666666666667 + 0.000999999999999985\mathrm{X}_1 + 0.015\mathrm{X}_2 - 0.145\mathrm{X}_3 + 0.00166666666666668X_1^2 + 0.00166666666666668X_2^2 + 0.0316666666666666X_3^2 + 0.000000000000000002\mathrm{X}_1\mathrm{X}_2 + 0.000000000000000009\mathrm{X}_1\mathrm{X}_3 - 0.000000000000000044\mathrm{X}_2\mathrm{X}_3 \tag{9}$$

$$Y_{2,coded} \text{ (Pole Body Flux Density)} = 1.52777777777778 - 0.52\mathrm{X}_1 + 0.027\mathrm{X}_2 + 0.061\mathrm{X}_3 + 0.157777777777778X_1^2 + 0.00277777777777776X_2^2 + 0.00277777777777775X_3^2 - 0.00875000000000005\mathrm{X}_1\mathrm{X}_2 - 0.01875\mathrm{X}_1\mathrm{X}_3 + 0.00624999999999998\mathrm{X}_2\mathrm{X}_3 \tag{10}$$

$$Y_{3,coded} \text{ (Rotor Yoke Flux Density)} = 0.508666666666667 - 0.016\mathrm{X}_1 + 0.058\mathrm{X}_2 + 0.019\mathrm{X}_3 - 0.00333333333333334X_1^2 + 0.00666666666666665X_2^2 + 0.00166666666666667X_3^2 - 0.00624999999999999\mathrm{X}_1\mathrm{X}_2 - 0.00125000000000001\mathrm{X}_1\mathrm{X}_3 + 0.00375\mathrm{X}_2\mathrm{X}_3 \tag{11}$$

$$Y_{4,coded} \text{ (Efficiency)} = 87.8417777778 + 5.002\mathrm{X}_1 - 1.63\mathrm{X}_2 - 0.603\mathrm{X}_3 - 4.4522222223X_1^2 + 0.137777777777779X_2^2 - 0.0872222222222223X_3^2 + 0.671249999999999\mathrm{X}_1\mathrm{X}_2 + 0.608749999999999\mathrm{X}_1\mathrm{X}_3 - 0.20625\mathrm{X}_2\mathrm{X}_3 \tag{12}$$

$$Y_{5,coded} \text{ (Shaft Torque)} = 9.50266666666667 - 0.608\mathrm{X}_1 + 0.205\mathrm{X}_2 + 0.081\mathrm{X}_3 + 0.5466666666666666X_1^2 - 0.00833333333333341X_2^2 + 0.0116666666666672X_3^2 - 0.1075\mathrm{X}_1\mathrm{X}_2 - 0.0825 + 0.0325\mathrm{X}_2\mathrm{X}_3 \tag{13}$$

$$Y_{6,coded} \text{ (Exciting Current)} = 28.9517777777778 - 16.857\mathrm{X}_1 + 0.947\mathrm{X}_2 + 1.466\mathrm{X}_3 + 11.4327777777778X_1^2 + 0.0627777777777773X_2^2 + 0.207777777777779X_3^2 - 0.77125\mathrm{X}_1\mathrm{X}_2 - 1.38625\mathrm{X}_1\mathrm{X}_3 + 0.30625\mathrm{X}_2\mathrm{X}_3 \tag{14}$$

$$Y_{7,coded} \text{ (Exciting Current Density)} = 7.00377777777778 - 1.691\mathrm{X}_1 + 1.744\mathrm{X}_2 + 0.305\mathrm{X}_3 + 2.31277777777778X_1^2 - 0.182222222222222X_2^2 + 0.0327777777777782X_3^2 - 0.03875\mathrm{X}_1\mathrm{X}_2 - 0.25125\mathrm{X}_1\mathrm{X}_3 + 0.10875\mathrm{X}_2\mathrm{X}_3 \tag{15}$$

The MATLAB program was used to code SSA and perform optimization. Number of search agents is selected as 30 and the maximum number of iterations is set to 1000 runs. These parameters are determined by referring to the literature and through a set of preliminary experiments [6, 9]. The problem was modelled as a constrained continuous optimization problem. The regression models given in Eqs. (9) - (15) were used for this purpose. The cost function and the constraints are presented in Eqs. (16) and (17), respectively. SSA algorithm was then run through these equations to optimize the design parameters of the generator (factors).

$$Z = -\left|\hat{Y}_{1,Target}/\max(Y_{i1}) - \hat{Y}_{1,coded}/\max(Y_{i1})\right| - \left|\hat{Y}_{2,Target}/\max(Y_{i1}) - \hat{Y}_{2,coded}/\max(Y_{i2})\right| - \left|\hat{Y}_{3,Target}/\max(Y_{i1}) - \hat{Y}_{3,coded}/\max(Y_{i3})\right| + \left|\hat{Y}_{4,coded}/\max(Y_{i4})\right| - \left|\hat{Y}_{5,coded}/\max(Y_{i5})\right| - \left|\hat{Y}_{6,coded}/\right. \tag{16}$$

$\max(Y_{i6})\big| - \big|\hat{Y}_{7,coded}/\max(Y_{i7})\big|$

Min Z s.t. $X_1 \in[-1,1]$; $X_2\in[-1,1]$; $X_3\in[-1,1]$ (17)

Note that the signs given in the equation of Z will be reversed and have to be "−" for maximization and "+" for minimization at SSA MATLAB code (see [9] for details). The target values for the responses are: Y_1=1 Tesla, Y_2=1.5 Tesla, Y_3=0.5 Tesla, Y_4= max (%), Y_5=min (N.m), Y_6=min (A), Y_7=min (A/mm^2). MATLAB cost function is given in Eq. (18) for better understanding of the readers.

$$Z = +\big|1/1.01 - \hat{Y}_{1,coded}/1.01\big| + \big|1.5/2.34 - \hat{Y}_{2,coded}/2.34\big| + \big|0.5/0.62 - \hat{Y}_{3,coded}/0.62\big| - \big|\hat{Y}_{4,coded}/89.56\big| + \big|\hat{Y}_{5,coded}/11.23\big| + \big|\hat{Y}_{6,coded}/62.87\big| + \big|\hat{Y}_{7,coded}/13.49\big| \quad (18)$$

After performing the SSA using MATLAB; optimum coded factor levels are calculated as 0.2490, -1, and -1 for the PBW, PSH, and PSW; respectively. To find the original factor levels, Eq. (1) operated in reverse. The uncoded factor levels are calculated as PBW= 14 mm, PSH=6 mm, and PSW= 30 mm. The response values for the optimum factor levels are calculated by using MINITAB. ANSYS MAXWELL simulation confirms the best design. Table 4 contains the confirmations and comparisons.

Table 4: Confirmations and comparisons of optimization results.

Responses	Target Value	MAXWELL (Y_i) (Observed Value)	MINITAB ($\hat{Y}_i$) (Expected Value)	PE (%)
Y_1: Pole shoe flux density (Tesla)	1	0.987	0.98	0.71
Y_2: Pole body flux density (Tesla)	1.5	1.358	1.34	1.34
Y_3: Rotor yoke flux density (Tesla)	0.5	0.442	0.44	0.45
Y_4: Efficiency (%)	max	89.13	90.57	1.59
Y_5: Shaft torque (N.m)	min	9.37	9.18	2.07
Y_6: Exciting current (A)	min	26.35	24.16	9.06
Y_7: Exciting current density (A/mm2)	min	5.15	4.71	9.34

According to comparisons given in Table 4, predicted results are very close to the ANSYS MAXWELL results. Overall PE for the 7 responses is less than 9.34%. This means that the design optimization process has been completed, and the design can now be used in mass production.

4. Conclusion

This research is focused on design optimization of 10 kW high speed generator. For this purpose response surface face centered design is used for designing the experiments and observations of this design are obtained from ANSYS MAXWELL simulations. Then mathematical modelling is performed to determine the relationship between the design parameters and the responses and SSA is used for optimization. The mathematical modelling is performed by using MINITAB and SSA coding is performed by using MATLAB. Optimum factor levels are calculated as PBW= 14 mm, PSH=6 mm, and PSW= 30 mm. According to the confirmations obtained through ANSYS MAXWELL simulations, the target values appear to have been largely met. Results indicate that SSA can be effectively used for this type of design optimization problems. This study can be extended for additional design parameters In the future researches. In addition, as a future research, producing a prototype 10 kW high-speed generator will also check the accuracy of the results.

Acknowledgements

We'd like to express our gratitude to Isbir Electric Co. for allowing us to use its facilities and software.

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