Design and Optimization of Tubular Linear Permanent Magnet Generator with Performance Improvement Using Response Surface Methodology and Multi-Objective Genetic Algorithm

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Abstract

Linear generators are electric machines which generate electrical energy from linear movement. Since these machines can lift gear wheel or power train, they have begun to be used widely nowadays. Since their working areas differ according to speed and power characteristic, this study contains design and optimization of tubular linear generator for free piston practices. The design performed response surface optimization through design variables was acquired as a result of sizing via interface. The association between the determined design variables and the sizes of generator output was examined. In addition, these sizes were used for objective functions of increasing efficiency, decreasing overall volume and increasing general performance and their optimum values were found by using Multi-Objective Genetic Algorithm. Initial and optimum design data were compared with Ansys Maxwell 2D. With overall performance increase, 22,78% decrease was seen in total mass, while 11,7% decrease was seen in cost. In addition, prototype linear generator was made in line with initial geometry data and it was applied with crank slider mechanism.

Keyword: Linear generator, permanent magnet, finite element, MOGA algorithm, optimization

1. INTRODUCTION

When the areas of usage for linear generators are considered (free piston applications, wave energy, stirling system, shock absorbers, vibrators, compressors, mobile chargers, vibration energy harvesting device, mobile lighting appliances, space applications), it can be seen that studies on this subject have been increasing each day. Since linear machines are generated from rotating machines, their working principles are not different. However, they are different in terms of their geometric structures, design equality and methods. As is known, electric machine designers should design by taking demands such as efficiency, total weight or local weight, cost, power density, etc. into consideration. In order to meet these goals, designers generally use optimization methods (Pattern Search, Sequential Nonlinear Programming, Genetic Algorithms, Response Surface, Monte Carlo etc.) with package programs. Ansys Maxwell is a program that has proven its validity and reliability in literature and it uses finite element method (FEM). In their study, Dalcali and Akbaba [1] examined the effect of parametric variation of pole arc offset distance on the performance of a Permanent-Magnet Synchronous Generator. Bouloukzaet al. [2] performed optimization by using Monte Carlo method. They showed that a good agreement is realized between the Ansys Maxwell 2D calculations and the analytical calculated values of the optimum design of slotted Halbach PMSM. Qinghua et al. [3] performed the optimization of permanent magnet synchronous motor (PMSM) by using Response Surface Method (RSM) and they produced the prototype of the motor. They showed that the numerical results obtained with this optimization method and the application results matched each other. Abbaszadeh et al. [4] performed the optimization of cavity gap and slide in order to decrease the stroke force with the help of RSM of BLDC. In the cogging torque of the optimized motor, a significant decrease is seen through the simulation result by FEM. Jolly et al. described work done on optimization of design of PMSMs using RSM and genetic algorithms [5]. Ghasemi[6] used RSM to reduce the stroke force of surface magnet synchronous motor. The result shows that the optimum values of RSM are more efficient than of those of the GA and particle swarm optimization in cogging torque reduction.Yu et al. [7] examined the effects of stator and rotor sizing variables of embedded permanent magnet synchronous motor on cogging torque with RSM. They made initial and optimum motor comparisons. Bremner [8] examined the effects of the basic geometrical proportions of embedded permanent magnet synchronous motor on the machine performance with RSM. Jabbar et al.[9] changed the rotor dimensions of embedded synchronous motor and performed optimization by using RSM and GA. Abbaszadeh et al.[10] examined the effects of the basic geometrical proportions of surface-insert permanent magnet synchronous machine on machine performance with RSM. Arehpanahi and Kashefi[11] used magneto static FEM analysis and RSM to reduce cogging torque reduction of Interior Permanent Magnet Synchronous Motor. Arslan et al.[12] performed the optimization of a torus type axial flux machine by using RSM and when they used this approach, the general performance of the machine was maximized and the cogging torque and weight continued to decrease. Saha et al.[13] stated that the efficiency improvement can be effectively achieved by designing the optimization of line-start permanent magnet motor rotor structure using the RSM. Ahn et al. [14] proposed that the approach is efficient to improve the performance of the optimal designed Permanent Magnetic Actuator and to reduce the number of experiments by the proposed RSM. The optimum design of the dual-permanent-magnet-excited machine was investigated by Jian et al. using RSM [15]. Hasanien et al. [16] performed optimization by using RSM and GA to improve the weight and thrust of transverse flux linear motor. Pourmoosa et al. [17] performed low speed one sided linear induction motor design. They performed optimization by using RSM to decrease motor weight and increase thrust. They found that simulation and application data matched to a great extent. In our previous studies on linear generator, Arslan et al. [18] formed a linear generator model through Ansys-

Maxwell with analytical equations designed in Matlab-Guide. They performed surface magnet tubular linear generator design and optimization. In line with the objective functions they determined, they used pattern research algorithm and obtained optimum sizing. Arslan et al. [19] examined magnetic flux density of the change in stator and rotor parts of the linear generator. Arslan et al. [20] performed inset magnet tubular linear generator design and optimization. They used genetic algorithm and Sequential Nonlinear Programming to reduce the cogging force. Wang et al. [21] performed optimization of tubular linear motor with decomposition-based multi-objective differential evolution particle swarm. Multi-Objective Genetic Algorithm (MOGA)'s single use can stretch to the area near an optimal Pareto front; however, it requires more computing time when compared with the multi-objective optimization approach. Parallelization causes a considerable decrease in computing time at each flowchart stage [22]. In this study, the software, called AnsysMaxwell2D, was used in the design calculation of tubular linear generator. The effects of tubular linear generator sizing variables on output variables were examined with correlation analysis. In addition, Ansys Workbench response surface method and MOGA were used to obtain optimum sizing in line with the objective functions determined. The initial design and the design obtained as a result of optimization were compared by using FEM.

2. Analysis of the association between the variable parameters of the generator and efficiency, power out, weight, cost and cogging torque

Regression is the approach of modeling the relationship between two or more variables functionally. The value of y variable is estimated for the values of x independent variable. Correlation is used to see whether there is relationship between two numerical variables, and if there is, to see the direction and size of this relationship. The mathematical model of tubular linear generator (Figure 1) is written under MatlabGui. Analytical sizing data are given in Table 1.

It is vital to find out the parameters that will have direct effect on the generator performance for optimization process since incorrectly chosen design variable or variables have an influence on the success of optimization. In addition, the determined input variables should not be associated with each other since this will cause to calculate the association between output parameters and input parameters. It is important to find out the association between input variables and output parameters and to find out to what extent input variable explains the output parameter. In line with this objective, optimization process will be more successful with the defined suitable input parameters. In addition, designers of electric machines choose the parameters which have a first degree influence on the geometry of motor/generator from studies in literature in general. However, variables are generally taken as inner diameter, outer diameter and pole pitch ratio. In this study, primary length and primary inner diameter widths were regarded as stable. Primary variables were determined as air gap width (*g*), thickness of magnet (*Lm*), slot-pitch ratio (*Beta*), pole-pitch ratio (*Alfa*), and primary yoke flux density (*Byp*). In order to find out the association between these design variables and design output parameters, Maxwell 2D *rz* linear generator model was formed with Ansys-Workbench. Geometric variables and dimension sizes were defined with design features. Control conditions were defined in Maxwell 2D *rz*. Input and output parameters (stroke, efficiency, power out, cost, volume, iron loss, etc) were determined from Maxwell 2D design research section. Parameter correlation analysis module was added. Research points were formed with the specified limits of input variables. Correlation analysis method was determined. Design samples were solved by the program until the specified calculation criterion was reached (Figure 4).

The association between input and output parameters is expressed in matrix form. The association between variables can be positive or negative. This association differs between +1 and -1. There is an inverse association if it is “-“ (as the input variable increases, output change decreases according to unit coefficient). There is a direct association if it is “+“ (as the input variable increases, output change increases according to unit coefficient). The variable itself and correlation are expressed with corner elements and get the +1 value. The association between other variables can have the positive or negative sates of the following values. These are defined as [23]; 0-0.19 No association; 0.2-0.39 weak association; 0.4-0.69 moderate association; 0.7-0.89 strong (high) association; 0.9-1 very strong association. Coefficient of determination, which is expressed as R^2, is known as the indicator that the total change in the dependent variable can be explained by the independent variable. R^2 variable differs between 0-1. A value close to 1 shows that a great part of the change in dependent variables is explained by independent variables [23].

In response to input design variables in Table 2, the associations between analysis process efficiency, power out, approximate cost and total volume have been defined in Figure 3. In the analysis performed for stroke, the maximum, peak-to-peak and root value of cogging force have been defined as output variable. The association between input variables and stroke change has been given in Figure 2:

As can be seen in Figure 2, although there is a moderate negative association between stroke and Alfa and g, there is a weak positive association between stroke and beta.

As can be seen in Figure 3, a very strong association is expected between mass, cost and volume. There is a negative strong association between *Beta* and mass, volume and cost. In addition, there is a positive high association between *Beta* and efficiency. There is a moderate association between *Alfa* and efficiency. There is a negative strong association between *g* and power out. There is a strong moderate association between *Lm* and power out and cost. *Byp* has very little association with mass, volume and cost. Having no association between specified design variables and forming moderate, strong and very strong associations with generator performance parameter is important for variables to participate in optimization.

3. **Optimization of Stroke and Objective Functions with Response Surface Method**

Designers want minimum cost when they want maximum efficiency and when they want maximum performance, they want minimum weight. Mathematical modeling has great benefits when the opportunity to have experimental works on the subject is limited, or in reaching results under conditions which require too many iterations. RSM, which is an application area of mathematical modeling, is one of the methods with partial factorial experimental or numerical application areas and it is a very important statistical method for the analysis of associations between different results obtained under different factors.

RSM uses statistical and experimental methods together. It is a group of serial processing applied to optimize the dependent variable value of independent variables. This method assesses independent variables as parameter and dependent variables as response or output. Moving in the direction of maximum increase or decrease to reach minimum or maximum level (maximum point desired) is the primary approach. The effects of independent variables on the response can be seen by decreasing the number of required experiments for optimization with RSM. While using RSM, it is important to choose the independent variables which are thought to influence the dependent variables the most in terms of getting correct results. The choice of variables can be determined through mathematical model or correlation analysis. Primary data given in the literature (pole pitch ratio, slot pitch, etc.) and the ranges in which these variables can be measured are found. Model equations used in RSM can be first or second degree equations. In electric machine studies conducted with RSM, second degree model equations are preferred more. Eq. 1 gives RSM design variables function and error:

$$y = f(x_1, x_2, x_3, x_4, x_5,\ldots, x_n) + \varepsilon \tag{1}$$

$y$is expressed as the response of the system, x_n is expressed as independent variables. Here, y can be expressed as efficiency, power out, stroke, etc. Design variables are given as Lm,g, alfabeta, Byp and ε error. The difference between the observed y value and the expected $y$value is given as the error:

$$y = f(x) + \varepsilon \tag{2}$$

Response surface models are expressed as second degree polynomials which include variables and the interactions of variables.

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=1}^{n} \beta_{\mathrm{ii}} X_i^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{\mathrm{ij}} X_i X_j + \varepsilon_0 \tag{3}$$

Here, β_0 is given as fixed model, β_i,$\beta_{\mathrm{ii}}$and $\beta_{\mathrm{ij}}$are given as variable coefficients and x_i and $x_j$are given as coded independent variables. After a second degree response surface model suitable for the variables is estimated, the levels of x_1, x_2, … , x_n variables, which optimize the estimated response variable, should be determined. This point which optimizes the response variable (if any) is found by taking the partial derivatives according to x_1, x_2, … , $x_n$variables and equating to zero. The designs generally used to reach optimum point are Central Integrated or Box Behnken Experimental designs. These designs are second degree models which contain second degree terms, that is, an association beyond the linear approach between independent variables and output value can be expressed. Figures 2 and 3 give the association between Ansys-Workbench and the parameters' correlation, response surface method and optimization. In addition, design explorer forms design points through input design variables defined in Ansys-Maxwell 2D*rz* and given in Table 2. Ansys Maxwell 2D *rz* tool is added in AnsysWorkbench. Within this tool, primary sizes of the generator, limiting conditions and analysis parameters are defined. Later, parameter correlation tool is added to Workbench and correlation matrices between input and output variables are obtained. RSM tool is added and the solution is realized. Here, MOGA is chosen as optimization method. The data obtained give the best result separately for each objective function (Table 3). Best results for each design (Table 4) were analyzed again at Ansys Maxwell 2D *rz*. FEM results obtained and analytical data were compared in Table 5. Figure 4 gives Ansys-Workbench and Maxwell 2D and analysis and optimization process.

It is possible to use the MOGA option for both Response Surface Optimization and Direct Optimization. In this study, it was used with response surface optimization. With MOGA, we can generate a new sample set or use an already existing set to provide an approach more refined than the Screening method. It can be used for all kinds of input parameters and it can also deal with multiple goals. A fast and non-dominated sorting method, which is an order of magnitude faster than conventional Pareto ranking methods, is conducted by Pareto ranking scheme. Lagrange multipliers and penalty functions are not required since constraint handling makes use of the same non-dominance principle with objectives. This provides feasible solutions to be ranked higher than infeasible solutions. In a separate sample set, the first Pareto front solutions are archived distinct from the evolving sample set, which makes sure that Pareto front patterns already available from earlier iterations get minimal disruption. By changing the Maximum Allowable Pareto Percentage property, the selection pressure (and, consequently, the elitism of the process) can be controlled to avoid premature convergence [24]. Below is the workflow of the MOGA optimization method:

The initial population is employed to operate the MOGA algorithm. When MOGA is operated, it produces a new population through cross-over and mutation. Following the first iteration, each population is operated after having reached the number of samples specified by the Number of Samples per Iteration property. MOGA steps to generate a New Population. In the new population, design points are updated and optimization is validated for convergence.

When either the Maximum Allowable Pareto Percentage or the Convergence Stability Percentage has been reached, convergence of MOGA takes place. The process continues to the next step if the convergence of MOGA does not take place. Optimization is validated for fulfillment of stopping criteria if it does not converge. In case of meeting the criterion of Maximum Number of Iterations, the process stops without having reached convergence. However, if the stopping criteria have not been met, in order to create a new population, MOGA is regenerated. MOGA generates a new population through stopping criteria. Until the convergence of optimization or fulfillment of the stopping criteria, validation is repeated in sequence. The optimization concludes if either of these things occurs [23]. According to the graph in Figure 6, increase in *Alfa* and *Beta* increases efficiency and power out. An increase in *Lm* increases both power out and cost. Increase in *Beta* will decrease weight, cost and volume. In addition, an increase in *Alfa* also increases cost.

Analyses showed significant effects of the association between *Beta* and *Alfa* on efficiency, weight and cost. Thus, it is important to determine the beta and *Alfa* ratios correctly for tubular and flat linear machines. For initial parameters, it is suitable to choose *Alfa* between the ranges of 0.68 and 0.73 and *Beta* between the ranges of 0.45 and 0.55. The change in magnet thickness with *Alfa* influences efficiency and cost significantly. Magnet thickness differs according to the feature of the magnetic equivalent circuit. While the thickness of the magnet decreases demagnetization risk, it also causes the core material to reach magnetic saturation. During the process of optimization with RMS, while benefit is derived from a feature, another feature is withdrawn. Analyses conducted showed that the change between magnet thickness and beta was in the form of if function (Fig. 7). There is local minimum and maximum in the if function. The optimum point of *Beta* can be taken as 0.5. While the magnet thickness and change of *Beta* does not influence efficiency significantly, it influences total generator weight and cost.

Figure 2 gives input variables and limits similarly. Objective functions given in Eq. 4 and 5 are defined separately. These objective functions are given as Design 1 efficiency maximum, Design 2 volume minimum, Design 3 cost minimum and Design 4 general performance boost (Efficiency/(Volume*Current density)) given in Table 3. For MOGA optimization, 600VA power out for each objective function:

$$A.F1 = \frac{\eta^{X_1}}{V^{X_2}.J^{X_3}} \text{ and } P_{\text{out}} = 600 \quad (4)$$

$$A.F2 = \frac{\eta^{X_1}}{M^{X_2}.J^{X_3}} \text{ and } P_{\text{out}} = 600 \quad (5)$$

$$A.F3 = \frac{\eta^{X_1}}{C^{X_2}.J^{X_3}} \text{ and } P_{\text{out}} = 600 \quad (6)$$

where $A.F1$, $A.F2$ and $A.F3$ are objective function, η is efficiency, V is volume, M is weight,C is cost, J is current density, P_{out} is output power in the design decided by desired values of X_1, $X_2$and X_3respectively. Here, in order to simplify the formula, X_1, X_2 and X_3 value sare equalized to 0 or 1. The simplified versions of objective functions given in Equations 4, 5 and 6 according to values of 0 and 1 from X_1, X_2 and X_3 and the target are given in Table 3. Here, two objectives were defined for each design in MOGA to maximize power out equal and functions for all targets.

Since the number of desired nominal value does not influence the optimization result in MOGA optimization method, the best proposed sizing data among the proposed four nominal values are given in Table 4:

Table 5 shows how much increase or decrease the obtained data show in terms of weight, cost and efficiency when compared with the initial design data. Here, while Design 1 showed 2.6% increase in total mass and no significant difference in cost, 2.8% increase was found in efficiency. In addition to 23.3% decrease in total mass and 13.9% decrease in cost, Design 2 showed 3.5% decrease in efficiency. Besides 21.1% decrease in total mass and 18.3%

decrease in cost, Design 3 showed no significant difference in efficiency. Design 4 showed 22.7% decrease in total mass and 11.78% decrease in cost. According to analytical and numerical calculation results given in Table 5 as RMS Optimization results, the highest efficiency is seen in Design 1.

Results are given in Table 4, showing that a good agreement is realized between the FEM calculations and the analytical calculated values of the optimum design. The most suitable situation is seen as Design 4, in which there is significant decrease in mass and cost and very little change in efficiency. In line with the design data given in Table 1, calculations of linear generator were made in the interface (Reference 19). However, when the size of the magnet obtained from MOGA results is considered, it is difficult to produce magnets specifically. Thus, generator geometry was formed depending on the initial design geometry data.

The images of crank slider mechanism are given in Fig.9 a,b and c. M43-24G geometry and magnetic rotor piece with sheet iron material for prototype are given in Fig. 9d and 9e. The prototype machine can be seen in the Fig.10 which is fabricated in the light of initial design. In Fig.10, the generator was driven with crank slider mechanism (Fig. 9b and Fig. 10b) prepared according to 4 pole asynchronous motor.

Numeric analysis results were compared by testing Prototype (unloaded) for 20Hz driving frequency (Fig. 11). Here, speed was calculated according to crank sizes given. It was found that the results of numerical analysis with Ansys-Maxwell and the results of the application were in parallel to a great extent. In the experimental study, nominal working speed and frequency value were not reached due to mechanic vibration.

4. **Conclusion**

Nowadays, studies on free piston motor-generator systems as range increasing unit for electrical or hybrid vehicles have become very important. In free piston motor-generator systems, it is vital to increase the efficiency of the electric energy produced in return for the fuel consumed. Thus, new approaches and methods to make the generator/motor designs in these systems compact, light and highly efficient are very important. In addition, since decreasing moving weight will increase mechanical frequency, it will have a direct influence on generator performance.

In this study, sizing optimization was performed for free piston practices by using response surface method through tubular linear generator model analytic results. Constraint values were tried to reach by making continuous iterations in line with sizing equations and objective function. These functions aim to increase efficiency, decrease cost, volume and total mass. Objective functions determined through response surface method were applied on MOGA analysis. In addition, it was found that Design 4, which included general performance, did not cause significant change in moving weight and caused 1.75% decrease in efficiency, as well as significant decreases of 22.7% in mass and 11.78% in cost. It was shown that response surface method and optimization method which contained MOGA were successfully implemented.

APPENDIX

$$l^2 = x^2 + r^2 - 2\mathrm{xrCos}\alpha \quad \text{(A.1)}$$

$$x^2 - 2\mathrm{xrCos}\alpha = l^2 - r^2 \quad \text{(A.2)}$$

$$x^2 - 2\mathrm{xrCos}\alpha + r^2\mathrm{Cos}^2\alpha = l^2 - r^2 + r^2\mathrm{Cos}^2\alpha \quad \text{(A.3)}$$

$$(x - rCos\alpha)^2 = l^2 - r^2(1 - Cos^2\alpha) \quad \text{(A.4)}$$

where

$$Sin^2\alpha = 1 - Cos^2\alpha \quad \text{(A.5)}$$

By taking the square root of two sides of the equality;

$$x - rCos\alpha = \sqrt{l^2 - r^2 Sin^2\alpha} \tag{A.6}$$

$$x = rCos\alpha + \sqrt{l^2 - r^2 Sin^2\alpha} \tag{A.7}$$

l length and r a crank radius is constant. The crank angle (α) varies from (0°-180) and x is the only variable that affects the piston position. If $\alpha = 0^\circ$, the piston is at the top point and position size is $l + r$. if $\alpha = 180°$, the piston is at the bottom point and position size is $l - r$.

Piston speed is a derivative of displacement;

$$v = \frac{dx}{dt} \tag{A.8}$$

Angular velocity;

$$\omega = \frac{d\alpha}{dt} \tag{A.9}$$

$$v = \frac{dx}{d\alpha} \cdot \frac{d\alpha}{dt} \tag{A.10}$$

$$v = \frac{dx}{d\alpha}\omega \tag{A.11}$$

If the derivation of the position of Equation A.7 is taken according to the alpha;

$$\frac{dx}{d\alpha} = -rSin\alpha + \frac{1}{2}\left(l^2 - r^2 Sin^2\alpha\right)^{-1/2} \frac{d}{d\alpha}\left(l^2 - r^2 Sin^2\alpha\right) \tag{A.12}$$

$$\frac{dx}{d\alpha} = -rSin\alpha + \frac{1}{2\sqrt{l^2 - r^2 Sin^2\alpha}}\left(0 - r^2 2Sin\alpha Cos\alpha\right) \tag{A.13}$$

$$\frac{dx}{d\alpha} = -rSin\alpha + \frac{r^2 Sin\alpha Cos\alpha}{\sqrt{l^2 - r^2 Sin^2\alpha}} \tag{A.14}$$

According to the equation A.11 and A.14 the speed can be calculated as follows:

$$v = \left[-rSin\alpha - \frac{r^2 Sin\alpha Cos\alpha}{\sqrt{l^2 - r^2 Sin^2\alpha}}\right] x\omega \tag{A.15}$$

REFERENCES

1. Dalcali, A., Akbaba, M. "Optimum pole arc offset in permanent magnet synchronous generators for obtaining lowest voltage harmonics", *Scientia Iranica. Transaction D,* Computer Science & Engineering, Electrical, **24**(6), pp. 3223-3230 (2017).
2. Bouloukzaa, I., Mourada M., Medoueda A., and et al., "Multi-objective optimization design and performance evaluation of slotted Halbach PMSM using Monte Carlo method", *Scientia Iranica D,* Computer Science & Engineering, Electrical, **25**(3), pp. 1533-1544 (2018)
3. Qinghua, L. I. U., Jabbar, M. A., and Khambadkone, A. M. "Response surface methodology based design optimisation of interior permanent magnet synchronous motors for wide-speed operation",*In Power Electronics, Machines and Drives, Second International Conference on ,* **2,** Edinburgh,UK, pp. 546-551 (2004).
4. Abbaszadeh, K., Alam, F. R. and Saied, S. A. "Cogging torque optimization in surface-mounted permanent-magnet motors by using design of experiment",*Energy Conversion and Management,* **52**(10), pp. 3075-3082 (2011).
5. Jolly, L., Jabbar, M. A. and Qinghua, L. "Design optimization of permanent magnet motors using response surface methodology and genetic algorithms",*IEEE Transactions on Magnetics*, **41**(10), pp. 3928-3930(2005).
6. Ghasemi, A. "Cogging Torque Reduction and Optimization in Surface-mounted Permanent Magnet Motor Using Magnet Segmentation Method", *Electric Power Components and Systems*, **42**(12), pp. 1239-1248 (2014).
7. Yu, J. S., Cho, H. W., Choi, J. Y. and et al. "Optimum design of stator and rotor shape for cogging torque reduction in interior permanent magnet synchronous motors", *Journal of Power Electronics,* **13**(4), pp. 546-551 (2013).
8. Bremner, R. D. "Rapid optimization of interior permanent magnet (IPM) machines using the response surface method and dimensionless parameters", Graduate Theses, Iowa State University, USA, (2010).
9. Jabbar, M. A., Jolly, L. and Qinghua, L. "Desıgn optımısatıon of permanent magnet motors usıng response surface analysıs", *In Digests 3rd International Conference on Electrical & Computer Engineering*, Dhaka, Bangladesh, pp. 28-30 (2004).
10. Abbaszadeh, K., Alam, F. R. and Teshnehlab, M., "Slot opening optimization of surface mounted permanent magnet motor for cogging torque reduction", *Energy Conversion and Management,* **55**, pp. 108-115 (2012).
11. Arehpanahi, M., Kashefi, H. "Cogging torque reduction of Interior Permanent Magnet Synchronous Motor (IPMSM)", *Scientia Iranica D,* Computer Science & Engineering, Electrical, **25**(3), pp. 1471-1477 (2018)
12. Arslan, S , Kurt, E , Akizu, O and et al. "Design optimization study of a torus type axial flux machine", *Journal of Energy Systems*, **2**(2), pp. 43-56. (2018).
13. Saha, S., Choi, G. D., and Cho, Y. H. "Optimal Rotor Shape Design of LSPM With Efficiency and Power Factor Improvement Using Response Surface Methodology",*IEEE Transactions on Magnetics*, **51**(11), pp.1-4 (2015).
14. Ahn, H. M., Chung, T. K., Oh, Y. H. and et al. "Optimal Design of Permanent Magnetic Actuator for Permanent Magnet Reduction and Dynamic Characteristic Improvement using Response Surface Methodology", *Journal of Electrical Engineering and Technology*, **10**(3), pp. 935-943 (2015).

15. Jian, L., Shi, Y., Wei, J. And et al. "Design Optimization and Analysis of a Dual-Permanent-Magnet-Excited Machine Using Response Surface Methodology", Energies, **8**(9), pp. 10127-10140 (2015).
16. Hasanien, H. M., Abd-Rabou, A. S. and Sakr, S. M., "Design optimization of transverse flux linear motor for weight reduction and performance improvement using response surface methodology and genetic algorithms", *IEEE Transactions on Energy Conversion*, **25**(3), pp. 598-605 (2010).
17. Pourmoosa, A. A. And Mirsalim, M. "Design Optimization, Prototyping, and Performance Evaluation of a Low-Speed Linear Induction Motor With Toroidal Winding", *IEEE Transactions on Energy Conversion*, **30**(4), pp. 1546-1555 (2015).
18. Arslan S., Gürdal O. and Akkaya Oy S. "The Design, Dimensioning And Optimization Of A 1 Kva Tubular Linear Alternator", *International Journal of Development Research*,**6**(12), pp.10550-10559(2016).
19. Arslan S., Gürdal O. and Akkaya Oy S. "The Determination of Effects of Primary and Secondary Geometry of Tubular Linear Generator", *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)*, **12**(1), pp. 6-11 (2017).
20. Arslan, S., and OY, S. A. "Design and Optimization of Tube Type Interior Permanent Magnets Generator for Free Piston Applications", *TEM Journal*, **6**(2), pp. 214-221(2017).
21. Wang, G., Chen, J., Cai, T. and et al. "Decomposition-based multi-objective differential evolution particle swarm optimization for the design of a tubular permanent magnet linear synchronous motor", *Engineering Optimization*, **45**(9), pp. 1107-1127 (2013).
22. Amdouni, I., El Amraoui, L., Gillon, F. And et al. "Multiobjective approach developed for optimizing the dynamic behavior of incremental linear actuators", *COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, **33**(3), pp. 953-964 (2014).
23. Alpar, R. "Uygulamalı İstatistik ve Geçerlilik-Güvenirlik", Detay yayıncılık, pp. 1-668, Ankara,Turkey (2014).
24. http://www.webcitation.org/query?url=https%3A%2F%2Ftr.scribd.com%2Fdocument%2F370055766%2FAnsys-Maxwell-18-Online-Help&date=2018-07-09

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Figure Captions

Figure 1. (a) 2D representation of geometrical sizing of tubular linear generator, (b) 3D representation of geometrical sizing of tubular linear generator

Figure 2. Correlation matrix between input variables and stroke

Figure 3. Correlation matrix between input variables and efficiency, power out, volume, cost and mass

Figure 4. RSM and optimization analysis process of tubular linear generator for an objective function with Ansys-Workbench

Figure 5. MOGA flow diagram

Figure 6. Local sensitivity change of basic variables in terms of output parameters

Figure 7. The influence of Lm-alfa-beta change on efficiency

Figure 8.The distribution of the magnetic flux density in the generator's length on Ansys Maxwell 2D *rz*

Figure 9.(a) r- radius of crank, l- length of connecting rod, α crank angle, (b) crank slider mechanism view in application, (c) measurement of length of connecting rod, (d) Sheet steel lamination, windings, secondary with permanent magnets, (e) prototype generator view

Figure 10.(a) Cranck slider mechanism, (b)Tubular Linear Permanent Magnet Generator Test Rig

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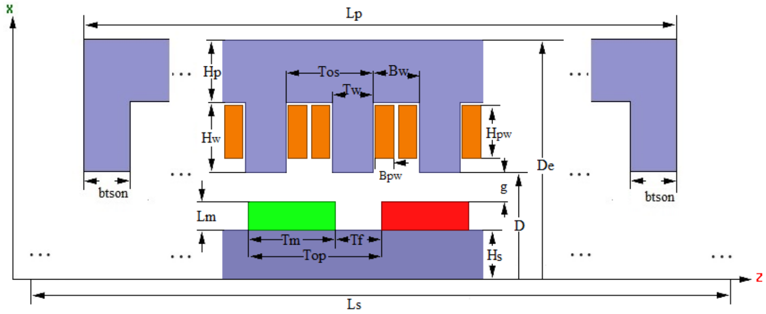
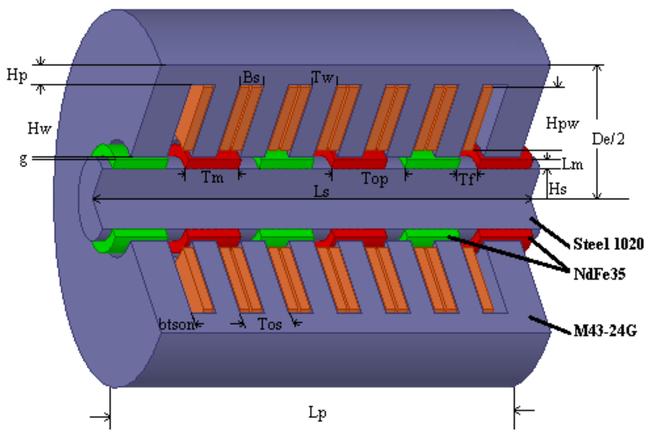
Table 3.Objectives of Designs

Table 4. Optimization results

Table 5.RMS Optimization results



(a)



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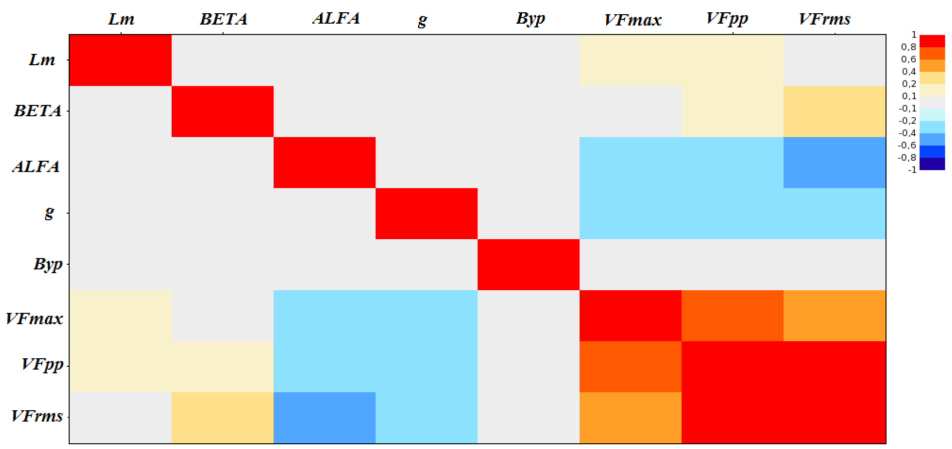

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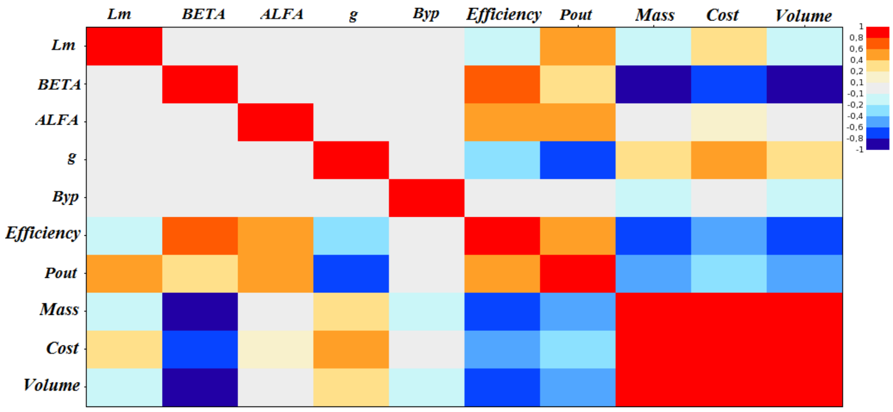

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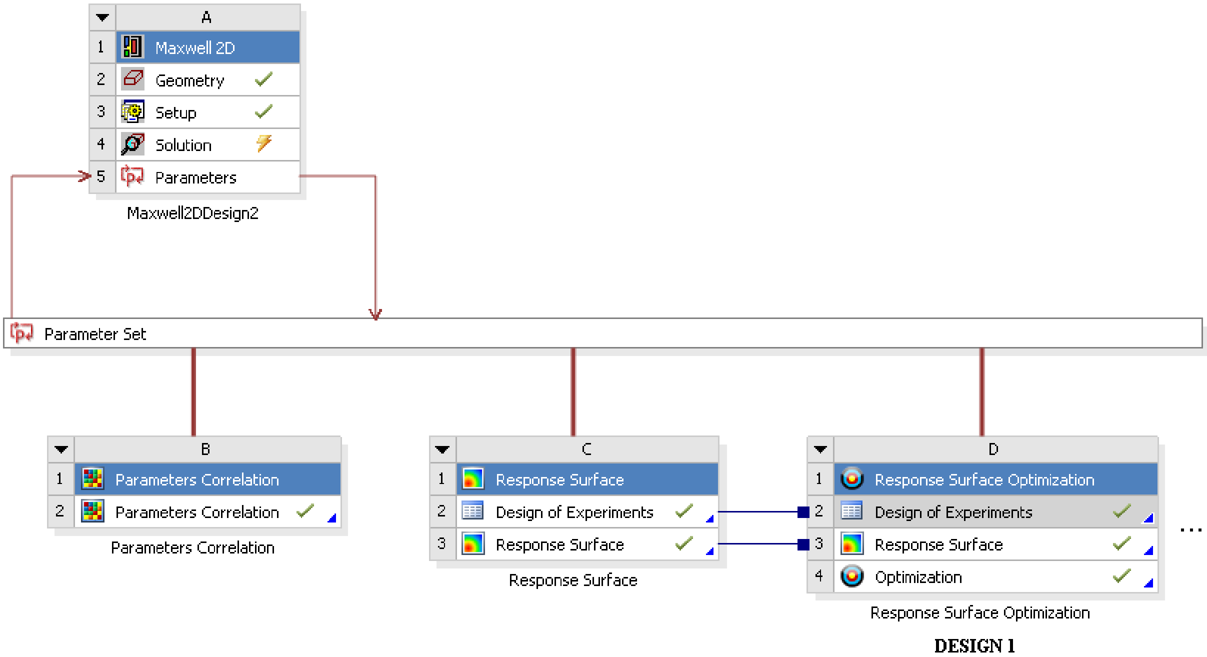

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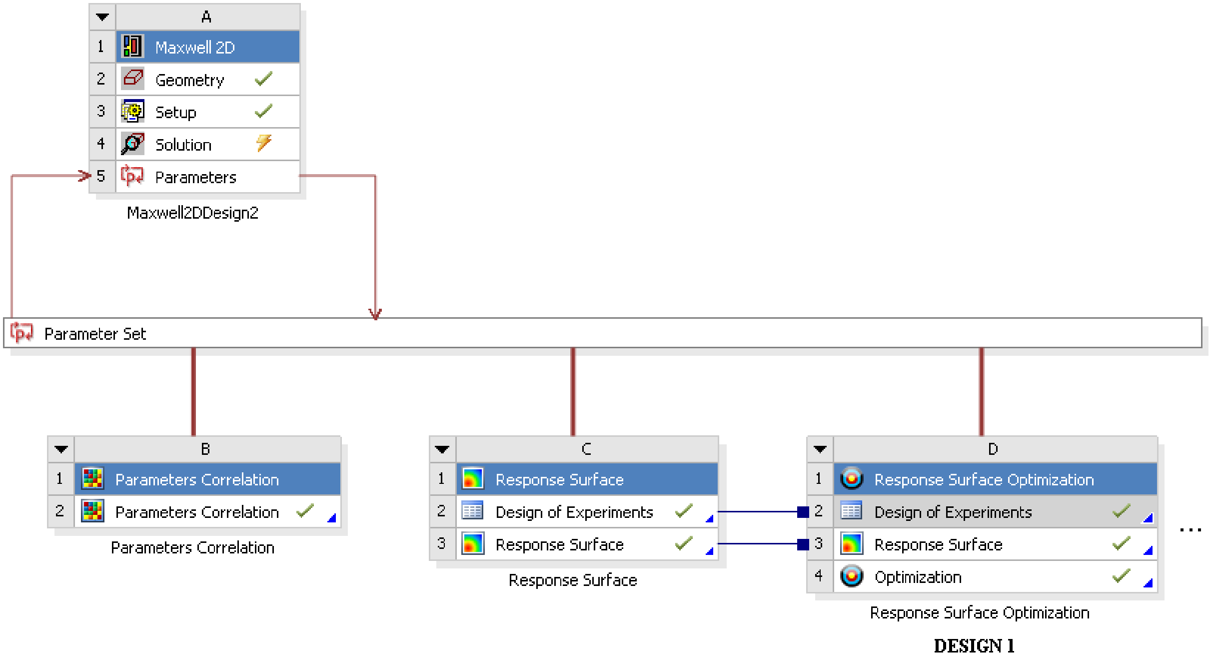

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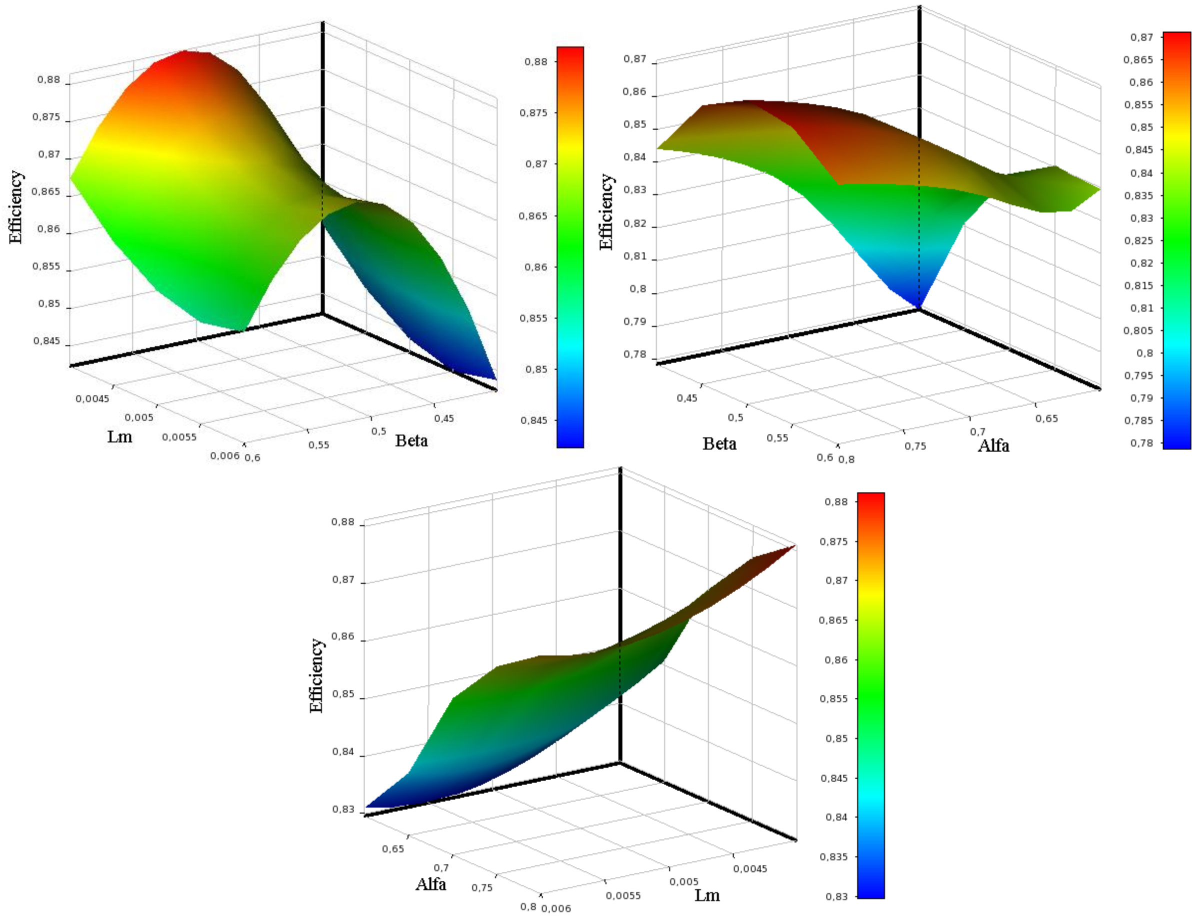

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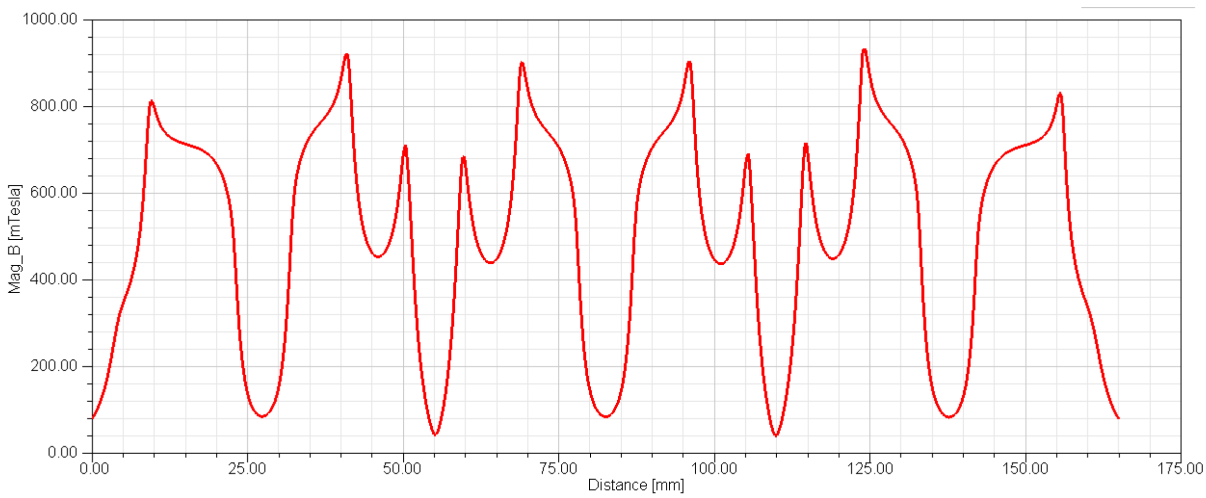

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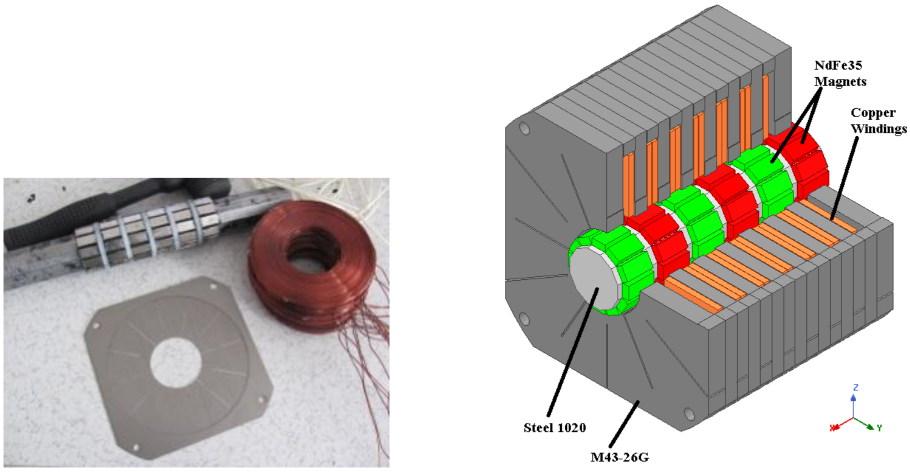
(a) (b) (c)



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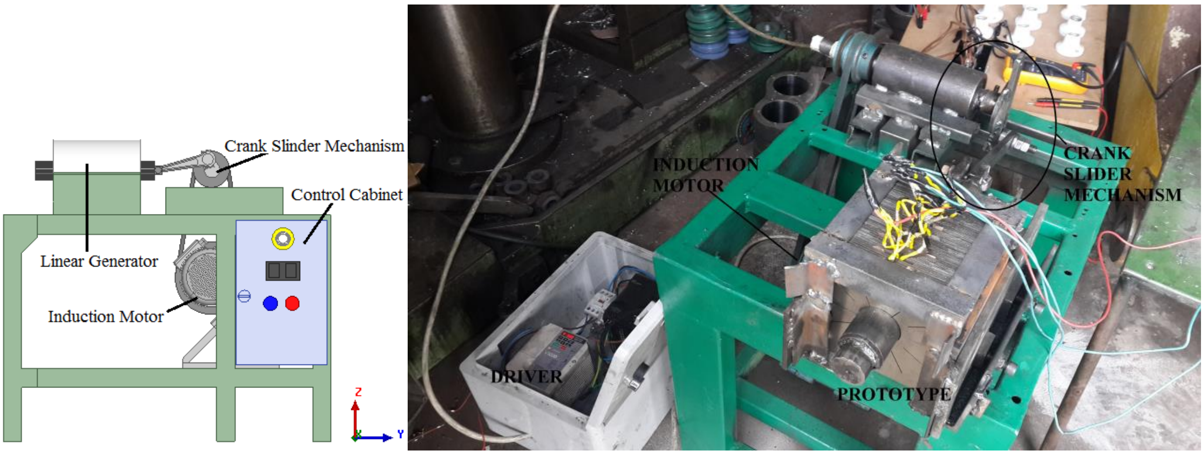

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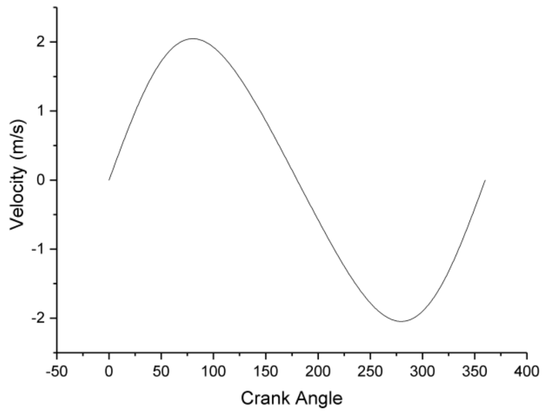
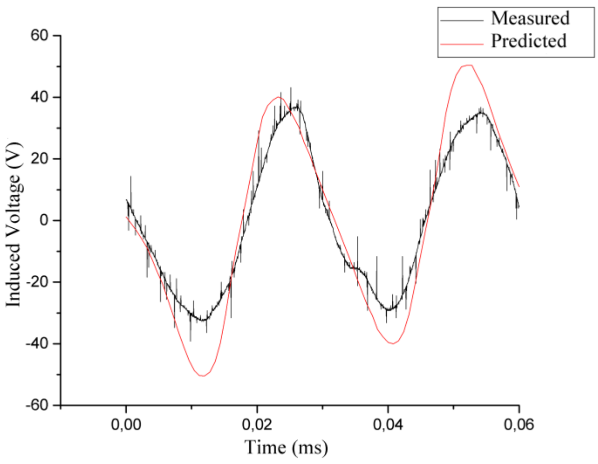


(a)



(b)

Figure 11.(a)Speed crank angle change, (b) the voltage value induced in open-circuit phase winding.

Table 1.Generator Input Design Parameters

Descriptions	**Value**	**Unit**	**Descriptions**	**Value**	**Unit**
Power	600	VA	Slot pitch	0.01833	m
Frequency	50	Hz	Lm	0.005	m
Stroke	0.0275	M	G	0.002	m
Rated Speed	2.75	m/s	Tm	0.0198	m
Shear Stress	2	N/cm^2	Tw	0.009166	m
Current Density	3	A/mm^2	Hw	0.04473	m
Induced Voltage	55	V	De	0.160	m
Alfa (Tm/Top)	0.72	-	Slot fill factor	0.6	-
Beta (Bw/Tos)	0.5	-	A coil winding number	76	-
Slot/Pole	6/4	-	Approximate cost of copper	30	Tl
Winding Factor	0.866	-	Approximate cost of magnet	250	Tl
Lowest Common Multiplier	12	-	Approximate cost of steel	10	Tl

Table 2.Input variables and margins

Input variables	**Initial design values**	**Search points (Min – Max)**	**Unit**
Alfa	0.7	0.6-0.8	-
Beta	0.5	0.4-0.6	-
L_m	0.005	0.004-0.006	m
g	0.002	0.0015-0.0022	m
Byp	1.8	0.6-0.8	T

Table 3.Objectives of Designs

Designs	Parameters	Objective	
		Type	Target
Design 1 X_1=1, X_2=0, X_3=0,	η $P_{\text{out}} = 600$	Maximize Seek Target	- 600
Design 2 X_1=0, X_2=1, X_3=0,	$\frac{1}{V}$ $P_{\text{out}} = 600$	Maximize Seek Target	- 600
Design 3 X_1=0, X_2=1, X_3=0,	$\frac{1}{C}$ $P_{\text{out}} = 600$	Maximize Seek Target	- 600
Design 4 X_1=1, X_2=1, X_3=1,	$\frac{\eta}{V\ .J}$ $P_{\text{out}} = 600$	Maximize Seek Target	- 600

Table 4. Optimization results

Input variables	Initial Design Analytical	Design 1 FEM	Design 2 FEM	Design 3 FEM	Design 4 FEM
Lm	0.005	0.00403	0.005524	0.0041038	0.005275
Beta	0.5	0.501	0.59486	0.59403	0.59913
Alfa	0.7	0.79033	0.63315	0.68248	0.68333
G	0.002	0.002058	0.0015203	0.0015147	0.0017788
Byp	1.8	1.815	2.1121	2.0857	2.1652

Table 5.RMS Optimization results

Output parameters	Initial Design Analytical	Design 1 FEM	Design 2 FEM	Design 3 FEM	Design 4 FEM
Moving weight (Kg)	2.38	2.51	2.37	2.55	2.39
Total weight (Kg)	19.09	19.6	14.64	15.05	14.74
Approximate cost (TL)	405.6	406.1	348.9	331.25	357.82
Power out(VA)	579.7	589.9	589	582	601
Efficiency	0.856	0.88	0.82	0.85	0.841