A New Shape Optimization Approach for Lightweighting Electric Machines Inspired by Additive Manufacturing

Preprint

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National Renewable Energy Laboratory

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A new shape optimization approach for lightweighting electric machines inspired by additive manufacturing

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Minimizing the mass in electric machines while maintaining superior performance is a new requirement for the advancement of drivetrains used in wind energy and electric mobility. Topology optimization (TO) for lightweighting electric machines using traditional approaches typically explores a restricted design space allowed by standard parametrizable geometry and manufacturing, while advanced methods, such as cell-based density approaches, suffer from a lack of robust manufacturability constraints during the optimization process. To overcome these drawbacks, we explore a grid-independent, boundary optimization where the outer shape of the magnet is parameterized using Bézier curves. We conduct a design of experiments (DOE) to study the effect of different magnet shapes on machine performance by varying the control points on the Bézier curves. A machine-learning-based surrogate model is constructed using the data from the DOE to quantify the relationship between the control points, air-gap torque, and mass. The control points are then optimized to maximize the torque density. The approach is used for minimizing electrical steel mass in the International Energy Agency (IEA) 15-MW radial flux direct-drive wind turbine generator. The new approach to shape optimization resulted in smooth and concise shapes that can be easily additively manufactured with up to a 20-ton reduction in electrical steel mass.

***Index Terms*—Additive manufacturing, Bézier curves, parametric design, topology optimization**

I. Introduction

OFFSHORE wind power generation is witnessing steady growth in recent years with more long-distance installations and the industry targeting larger (15-20 MW) turbines for 2030 [1]. As strategies to develop reliable generator technologies emerge, a key focus remains on increasing torque density [1]–[3] to reduce the size, weight, and drive systems' capital expenditure. Achieving improvements in reliability and efficiency by the use of direct-drive generators continues to put upward pressure on capital costs for some original equipment manufacturers, requiring specialized machining and lifting capacity for manufacturing, operations, and installation [4]. Realizing higher torque densities with direct-drive generators will require new approaches to design and manufacturing in order for lightweighting to be competitive.

Designs for lightweighting electric machines broadly fall into three categories—parametric optimization, topology optimization, and shape optimization (Fig.1). *Parametric optimization* is a popular approach for designing direct-drive generators with respect to predefined geometric parameters [5]. However, since the initial shape of the geometry is fixed, the solution space for finding lightweight designs will be limited as allowed by standard geometries and 2D manufacturing. Nonparametric optimization techniques, such as *topology optimization* (TO), have been used to optimize the material layout of an initial design using a grid whose elemental property serves as the design variable [6]. Due to the complexity of various materials, variation of excitation, and other issues, the optimal spatial and temporal distribution of materials is closely dependent on the starting design [7]. The dependence on a grid and the need for numerous fitness evaluations often requires accelerated optimization using advanced machine learning (ML) techniques [8]. Further, several drawbacks remain, including the appearance of intermediate material states, the presence of checkerboard patterns with corner-contact or jagged boundaries that require extraneous post-processing [9] before fabrication—even when using the most advanced techniques, such as 3D printing, proposed by the authors in [10]. Because no geometrical information is embedded in the design, it is impossible to control curvatures of resulting boundaries. Further, the use of rectangular cells is not efficient because it can cause electromagnetic field concentration around sharp corners [11].

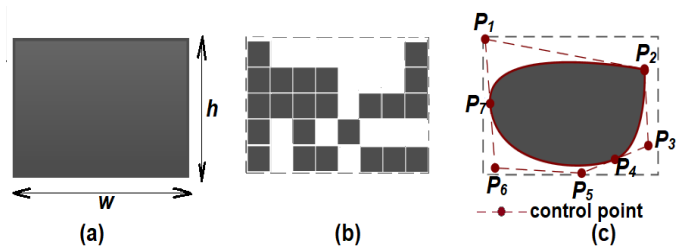

Fig. 1. Optimization approaches adapted from [7]: (a) Parametric optimization, (b) topology optimization, and (c) shape optimization.

A less commonly used approach is *shape optimization*, where geometric parameters of some boundary points serve as design variables. The selection of boundary points is usually based on experience or analytical calculation [12], which increases the difficulty in the realization and errors in geometry caused by mesh generation. Boundary representations include the use of nonuniform rational B-splines (NURBS) [13] followed by some sort of a shape-sensitivity analysis [14]. However, advanced techniques for derivation are needed. Moreover, if performance parameters have a one-to-one correspondence with node points, the design procedure may produce a zigzag shape or loss of continuity [14]. Merkel

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et al. [16] performed a gradient-based shape optimization for a permanent magnet synchronous machine using B-splines and continuum shape sensitivity analysis. The spline-based geometry allowed for easy integration in commercial finite element analysis (FEA) software and improvements in torque profile. Faezian et al. [15] used B-spline representation for minimizing vibration in a switched reluctance motor. The resulting shape made it impossible to use commercial software to calculate air-gap torque distribution; thus, separate programming was necessary. The optimized B-spline geometry needed wire-electro-discharge machining that can be expensive for mass production.

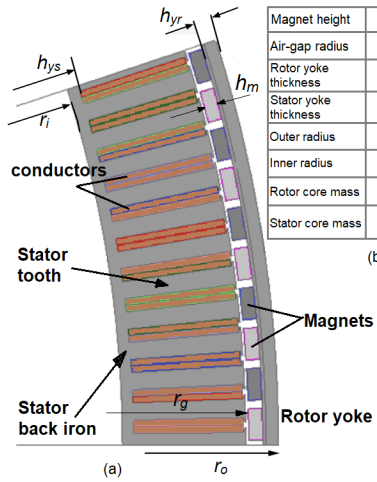
In an effort to bridge the gap between TO and advanced manufacturing—and to identify the best designs in terms of mass reduction and optimization time—we explore a new, grid-independent, free-form parametric, shape optimization using Bézier curves. The goal is to optimize the 2D shape of active parts of the International Energy Agency (IEA) 15-MW radial flux p ermanent m agnet s ynchronous g enerator [17] to produce 3D-printable designs that are better in terms of both air-gap torque and weight.

We conduct a design of experiments (DOE) to study shape sensitivities on generator performance by varying the control points on the Bézier curves and assigning material to the regions bounded by the curves. Each resulting topology in the DOE is imported into a parametric 2D CAD environment to build solid models that are analyzed by transient magnetic FEA. Lightweight designs are searched efficiently u sing a sequential training and optimization that couples magnetic FEA with a parametric CAD environment and an ML-based surrogate model.

This paper is structured as follows: In section II, the generator model and optimization regions are introduced. Section III presents the methodology, shape parametrization, and discretization for the rotor and stator back-iron using Bézier curves. In Section IV, we present and discuss the numerical results of optimization of air-gap torque. We conclude the paper by explaining the advantages and opportunities in lightweighting, using the new optimization process.

II. Generator Model and Optimization Regions

The IEA 15-MW generator is an outer-rotor, radial-flux, permanent-magnet machine [10] originally designed by parameter optimization with total generator mass as a minimization objective. The stator teeth, rotor, and stator yoke were shaped to guide as much flux produced by magnets via the air-gap as well as positively contribute to the structural stiffness against air-gap deformation. The rotor core to which the magnets are bonded serves as the yoke that is attached to a structural disc attached to a shaft. Fig. 2 shows an 18° sector of machine, including the magnets, back-iron, and stator teeth. The machine has a total mass of 371.51 tons, with a contribution of up to 180 tons from electrical steel alone. In a prior study by the authors [10], a preliminary TO was performed on the rotor core of this generator using a 12 x 4 grid discretization (with 12 and 4 representing the circumferential and radial distribution of quadrilateral elements behind a pole pair) that helped identify up to 15 tons in weight reduction.



Magnet height	h_m	58.39	mm
Air-gap radius	r_g	5,080	mm
Rotor yoke thickness	h_{yr}	63.62	mm
Stator yoke thickness	h_{ys}	46.52	mm
Outer radius	r_o	5,202	mm
Inner radius	r_i	4,567	mm
Rotor core mass	$M_{rotor\text{-}core}$	34.29	tons
Stator core mass	$M_{stator\text{-}core}$	153.21	tons

(b)

Fig. 2. (a) A section of the IEA 15-MW generator model. (b) Mass and dimensions of the rotor and stator core.

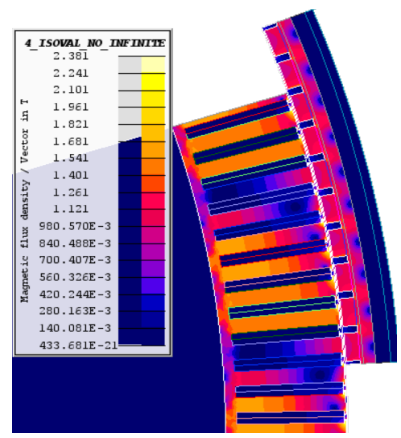


Fig. 3. The magnetic flux density contour at rated torque conditions. The maximum rotor magnetic loading at rated torque condition was 1.54 Tesla [10].

Because the goal of this paper is to optimize the 2D shapes of active parts without the use of a grid, we re-investigated the regions represented by the thicknesses of the rotor and stator yoke h_{yr} and h_{ys} and compare the results against the grid-based approach. Due to periodicity, we restrict the shape optimization to a span of one pole-pitch (θ_e = 3.6°) covering two poles, two stator-slots, and teeth. The rest of the design is constructed by repeating the patterns through 360°. Fig. 3 shows the magnetic-flux density contour obtained by transient electromagnetic 2D simulation with the rotor displaced by 3.6°. This was helpful in locating the regions of low magnetic loading by simulating the full load condition of the generator at rated speed (i.e., 7.56 RPM) [17], while also accounting for any transient effects due to the shape change effectuated behind the pole pairs and their impact on the the average air-gap torque as the rotor poles traversed the stator.

III. Shape Parametrization using Bézier Curves

Bézier curves are a popular class of free-form parametric curves within CAD systems that allow easy alterations to geometry. Compared to NURBS or B-spline-based models,

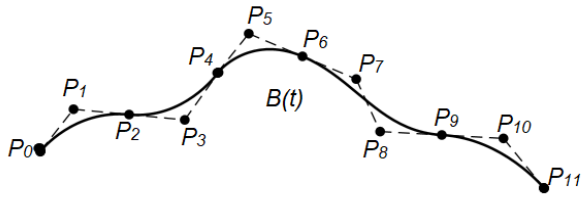


Fig. 4. A 10th-degree Bézier curve.

Bézier curves have fewer control parameters, are mesh independent, and design variables are reduced significantly so that optimization problems can be solved efficiently using small-scale optimization algorithms, such as sequential quadratic programming [18]. Because Bézier curve possesses attractive properties such as continuity, and local control ability, the optimal shape obtained with Bézier parametrization can be easily manufactured by transferring control points to commercial CAD software or 3D printers. These curves find numerous applications in computer-aided geometric design, particularly for wind turbine and propeller blades, car bodies, ship hulls, and aircraft. Because they present opportunities to integrate parametric-CAD-based design, shape optimization, and 3D printing, we investigated the Bézier parametrization for lightweighting the IEA 15-MW generator. A simple 10th-degree Bézier curve (Fig. 4) was used to define and shape the stator and rotor boundaries with 11 control points (Fig. 5). Adjacent curves have the second degree of continuity at the common control points. The first and last control points, P_0 and P_n, respectively, are the endpoints of the curve, and a set of intermediate points that do not lie on the curve define its shape. The number of control points was chosen to be consistent with the angular locations of the 12 circumferentially distributed elements that were used for discretization using the grid-based approach. However, since the 1st and 12th nodes were constrained by symmetry, this required 11 points. The equation of the curve passing through control points P_i and P_{i+1}, defined using de Casteljau's algorithm, is:

$$B(t) = \sum_{i=0}^{n} P_i b_{i,n}(t), \;\; t \in [0,1] \tag{1}$$

where *n* is the order of the curve (n = 1 for linear, 2 for quadratic, etc.) and *$b_{i,n}(t)$* is a set of Bernstein basis polynomials of degree n given by:

$$b_{i,n}(t) = \binom{n}{i} (1-t)^{n-i} t^i, i = 0, ..., n \tag{2}$$

Each of the 11 control points represented the radial distances from the origin. Let $B_1(t)$ and $B_2(t)$ represent the rotor and stator boundaries, respectively, and are continuous functions of radii (r and s) and angular position such that $r_o \geq$B$_1(t)$ $\geq$r$_g + h_m + 12.00$ over an interval $[t_o, t_{11}]$ and $r_i + h_{ys} - 12.00$ $\geq$B$_2(t)$ $\geq$r$_i$ over an interval $[t_o, t_{11}]$. Then, by transforming t in the polar coordinate system by scaling $\rightarrow \frac{\pi \theta_e t}{180}$ (where θ_e is the electrical angle) and substituting $t = rcos\theta$, the mass of the rotor core can be obtained from the areas under the curves by integration as:

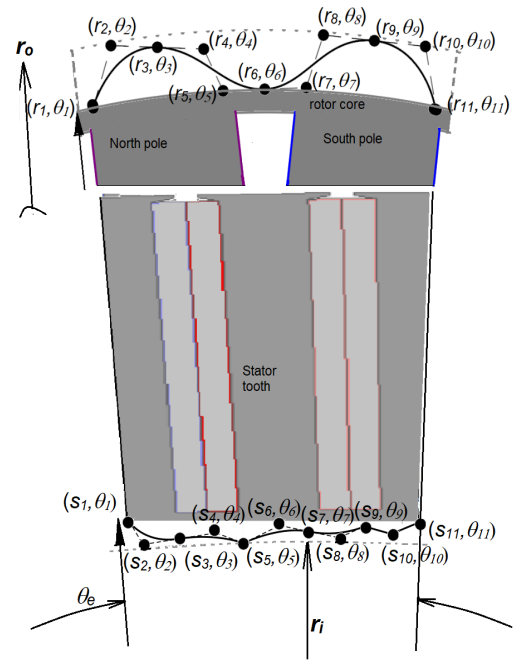


Fig. 5. Bézier rotor and stator core parametrization (dashed lines represent the original boundaries of the rotor and stator back-iron).

$$M_{Bézier-rotor} = \frac{100\rho L}{2} \left[\int_{\theta_1}^{\theta_{11}} (r_1(\theta))^2 d\theta - \int_{\theta_1}^{\theta_{11}} (r_g + h_m)^2 d\theta \right] \tag{3}$$

The mass of the stator core can be computed as:

$$M_{Bézier-stator} = M_{const} + \frac{100\rho L}{2} \left[\int_{\theta_1}^{\theta_{11}} (r_i + h_{ys})^2 d\theta - \int_{\theta_1}^{\theta_{11}} (s(\theta))^2 d\theta \right] \tag{4}$$

where ρ is the mass density of electrical steel, L the stack length (= 2.1695 m), and M_{const} is the mass of the unaltered region of stator core, including the teeth.

IV. Methodology and Assumptions

Fig. 6 shows the design optimization flowchart with the main parts of the algorithm implemented in Python. The algorithm was first applied to rotor core and used in successive optimization of stator back-iron. As a first step, we perform an initial DOE to create meaningful data sets that capture the sensitivities of air-gap torque distribution and magnetic loading to different rotor and stator boundaries. The DOE combinations of the control points were generated by Latin-Hypercube-sampling technique available under randomized design package as part of python's PyDOE2 package [20]. For the construction of the response-surface, a multivariate regression model was utilized to generate feature matrix consisting of all polynomial combinations of the features with a 6th degree polynomial.

The control points were allowed to be displaced only in radial direction at 10 angular positions from 0°–3.6° with $\Delta\theta$ = 0.36°. Only single-material designs were pursued for the present study, and the specifications for Fe-3.0Si steel for both rotor and stator core were identical to values reported in reference [10]. We intend to explore a gradient-based optimization on the shape parametrization so that the displacement of every node on the Bézier curve is a control variable. To avoid highly oscillatory shapes, regularization of the gradients, or computation of shape derivatives [12], we implement a CAD-based method to work directly with the control variables—both for the CAD-model description as well as optimization. This is an indirect way of optimizing the CAD-model sensitivity filtering that is needed for free-form shape optimization problems with rich design space of interest.

At least 1,000 sets of bézier curves were generated, and each set was used to build parameterized CAD models that were automated using the application programming interface (API) capabilities of OpenCASCADE [21]. 2D modeling and data exchange features from the pythonOCC project [22] were used to enable the preprocessing for linking CAD models and the DOE. This linking was used for both CAD construction of the Bézier shapes as well as for creating CAD models of optimized designs. Initially, each set of 1,000 CAD models was imported, meshed, and analyzed by transient magnetic FEA in Altair®-Flux® [23]. The regions bounded by the curves assumed the same material as baseline electrical steel. The air-regions surrounding the shapes were redefined to accommodate the changes in core shape. The field equations were solved for 50 steps ($\delta\theta = 3.6/50$). The design data and results for maximum average air-gap torque and maximum flux density were used to train an ML-based surrogate model for predicting designs of desired performance. The rotor control points were optimized by augmenting the training data set with newly optimized designs obtained by the sequential least squares programming method [19] coupled to an automated CAD-based FEA. The final optimal core shape that met the performance contraints served as the starting design for stator-core optimization that followed a workflow similar to the rotor core. Based on prior study by the authors in [10], core shaping is expected to result in a torque reduction, increase the magnetic loading, and, hence, the core losses. The maximum allowable reduction in torque was constrained to 0.5%, and the maximum permissible magnetic loading was set to be 1.2 × saturation magnetization (B_{sat}) of the baseline electrical steel in the case of rotor core. It was assumed that the topological changes in the stator core will not significantly impact the rotor-core magnetic loading.

A. Optimization objectives

The optimization objectives were a function of design variables (i.e, position of control points) and formulated in three ways that allowed for the maximization of average air-gap torque and minimization of electrical steel mass. We constrained the maximum rotor-flux density to the maximum magnetic loading obtained from grid-based optimization [10]. (This approach constrained the maximum loading to the saturation-flux density at 48 locations and up to a 20% increase in loading over one electrical cycle.) Table I lists three optimization objectives for the rotor core. A similar approach was adopted for the stator core.

TABLE I
OPTIMIZATION GOALS AND CONSTRAINTS

Objective function	Constraints
$\max_{P_i} f_{1rotorcore} = \frac{T_{mean}(P_i)}{M_{Bézier-rotor}}$ i=0,1,2,..10	$B_{max} \leq 1.2 \times B_{sat}$
$\min_{P_i} f_{1rotorcore} = M_{Bézier-rotor}$	$T_{mean}(P_i) \geq 20.48$ $B_{max} \leq 1.2 \times B_{sat}$
$\max_{P_i} f_{1rotorcore} = T_{mean}(P_i)$	$M_{Bézier-rotor} \leq 20.0$ $B_{max} \leq 1.2 \times B_{sat}$

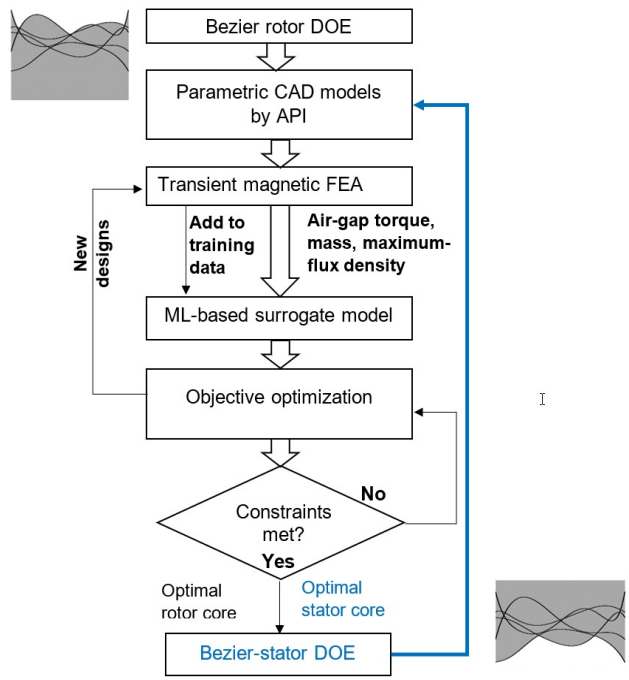


Fig. 6. Optimization flowchart.

B. Results

Fig. 7 presents the optimal designs for rotor core shapes obtained from the CAD-based boundary optimization with the three different objective function formulations presented in Table I. Each solution was identified from a data set accumulated from at least 50 iterations of sequential training and response optimization by a gradient-based search. Also presented for comparison is an optimal design obtained from a grid-based density TO of the same rotor core from a previous study by the authors in reference [10]. That design is a solution from a conventional multivariate regression model that maximized torque (and constrained mass to 20 tons). The region behind a pole pair was discretized by a 12 × 4 grid, with each of the cell elements assuming either air or electrical steel for material. The optimal solution resembled a double staircase pattern with minimum use of active material necessary for flux guiding. If jagged edges were to be ignored,

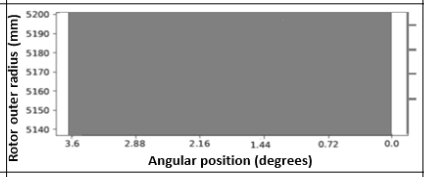
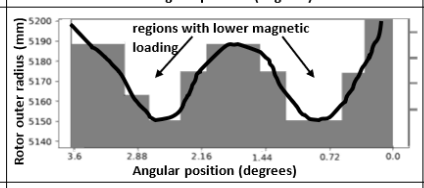
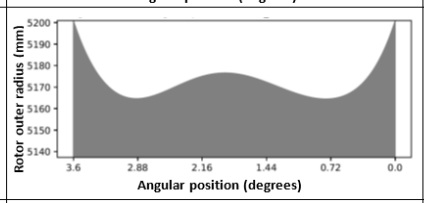
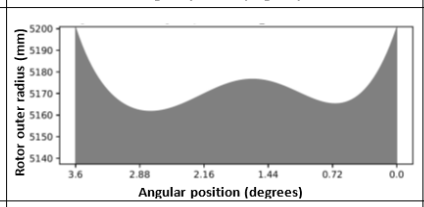
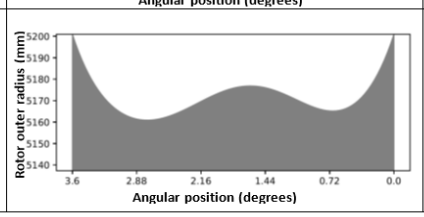
Design	Rotor core pattern	$M_{rotor-core}$ (tons)	Torque (MNm)	
Baseline design		34.28	20.48	
Optimal result from grid-based TO		19.95	ML 20.48	FEA 20.37
Objective function f_1		18.95	ML 20.48	FEA 20.41
Objective function f_2		18.57	ML 20.43	FEA 20.4
Objective function f_3		18.5	ML 20.48	FEA 20.4

Fig. 7. Optimized rotor core designs from grid-based TO and .

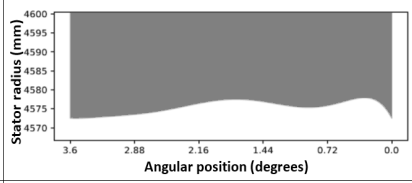
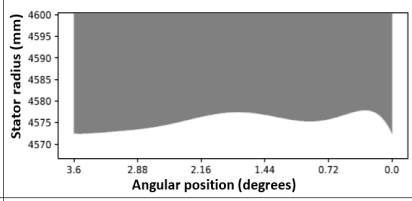
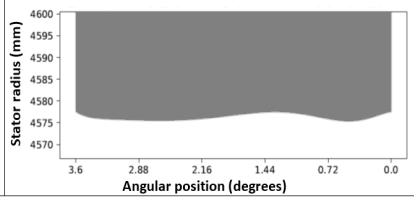
Design	Stator back-iron pattern	$M_{stator-core}$ (tons)	Torque (MNm)	
Objective function f_1		149.02	ML 20.48	FEA 20.41
Objective function f_2		149.02	ML 20.45	FEA 20.41
Objective function f_3		148.65	ML 20.46	FEA 20.4

Fig. 8. Optimized stator back-iron using boundary optimization.

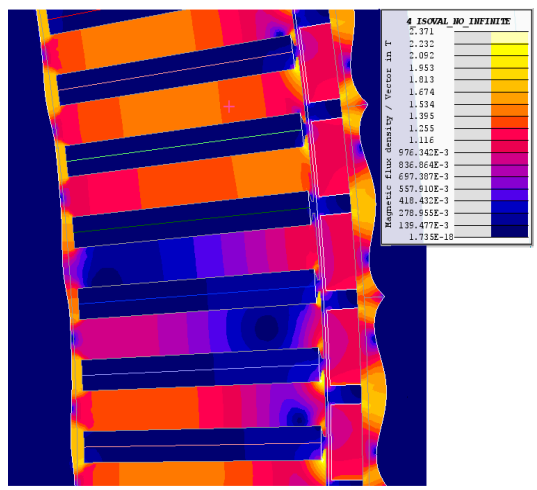


Fig. 9. Flux contour plot with optimized rotor and stator back-iron.

then connecting the centers of edges results in a wave-like pattern with two troughs and a crest. To the knowledge of the authors, manufacturing of wave-shaped rotors have required excessive machining and tooling that have been expensive for mass production and resulted in high scrap rates [14]. 3D printing can overcome this challenge by allowing near-net shaping by direct printing from bézier-parametrized shapes in 3D CAD models. Further, 3D printing will also enable multimaterial printing that will allow composite designs such as combination of low-loss and high strength electrical steel materials that will provide better trade off in terms of mass as well as efficiency.

Results from Bézier curve-based density representation successfully suppressed the artifacts of grid-based methods and resulted in smooth, curvier designs with troughs and crests at locations that were slightly offset from locations preconceived from the grid-based approach. The torque predictions were found to be better than that of the grid-based design with root-mean square error $<1\%$ of the mean torque. With upto 15.78 tons reduced from the rotor core, the shapes were found to be lighter than the grid-based design by up to 1.45 tons. The maximum-flux density loading for all three shapes across the entire rotor core for the full electrical cycle was lower than 2.2 Tesla.

Fig. 8 presents optimal designs for stator-back iron shapes obtained with optimized rotor core. The formulations for objective functions were identical to rotor core with mass replaced by $M_{Bézier-stator}$ and upper limit of mass constrained to baseline stator core mass, which included the mass of the teeth.

Both objective functions f_1 and f_2 resulted in similar designs, while up to 4.56 tons of weight reduction for the stator core was identified as feasible without compromising performance.

Fig. 9 shows flux density contour for the optimized cores for the IEA 15-MW generator with an overall mass reduction of 20 tons. The authors envision additional opportunities for

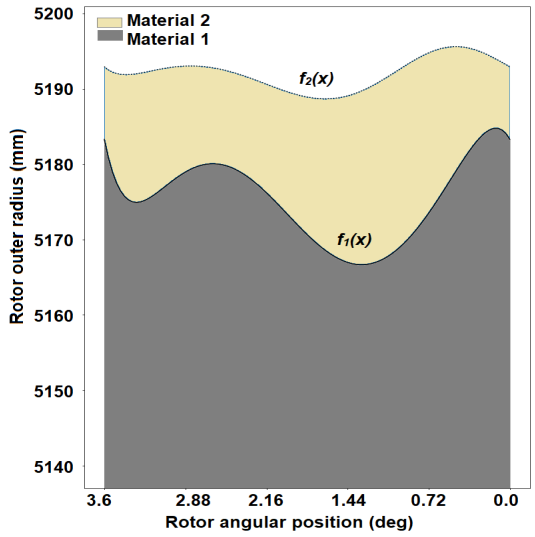


Fig. 10. A two-layered multimaterial rotor core design parametrized using two Bézier curves $f_1(x)$ and $f_2(x)$.

weight reduction from the stator teeth, which would require a coupled magneto-thermal-structural analysis and multimaterial designs by additional set of Bézier curves (e.g., two sets of curves can help realize layered designs, as shown in Fig. 10).

V. Conclusion

This paper presented a novel, CAD-based, ML-powered approach for topology optimization of the IEA 15-MW direct-drive generator with space Bézier curves representing its magnet boundaries. It has been demonstrated with proper choice of control points that Bézier curves act as intrinsic filters to identify better-performing lightweight designs that are free from jagged or zigzag shapes that can otherwise result in excessive flux concentrations around sharp corners.

Coupling Bézier-parameterized shapes with optimization and FEA presents a novel pathway to accelerated exploration of the electric machine's design space and realization of complex geometries in commercial FEA software and 3D printers. This will be particularly helpful in overcoming problems with complex geometries with insufficient measures to accommodate another component, material, or welding process.

We identified at least 20 tons of weight reduction by reshaping the boundaries of back-iron of the rotor and stator from conventional circular arcs to wave-like patterns. Further work is planned in exploring Bézier representation in robust formulation for lightweighting different parts of the generator, including the stator teeth, hard magnets, and structural parts, and considering thermal and structural domains of the problem. This could open up exciting opportunities in multimaterial design and 3D printing of electric machines.

Contributions

Latha Sethuraman designed the coupling of parametrized CAD models with magnetic FEA and TO, analyzed the results, and wrote the manuscript; Ganesh Vijayakumar developed the Bézier parametrization, provided inputs to sequential training and optimization, and edited the manuscript.

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