**2D Hybrid Magnetic Field Model Performance Optimization for Linear Induction Motor**

By

**Michael Thamm**

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Submitted to the Faculty of Graduate Studies

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2D Hybrid Magnetic Field Model Performance Optimization for Linear Induction Motors

by

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# DECLARATION OF CO-AUTHORSHIP/PREVIOUS PUBLICATION

I hereby declare that this thesis incorporates material thatis result of joint research, as follows:

This thesis contains the outcomes of publications which include the contributions of co-authors who were/are post-doctoral fellows, graduate students or associate professors under the supervision of Dr. Narayan C. Kar. In all cases, only my primary contributions towards these publications are included in this thesis. The contribution of co-authors was primarily with respect to refinement and editing process. In Chapter 2, I was the co-author in which I was actively part of experimental testing and assisted in data analysis. The model developed by the primary author, A. Fatima, in this publication is used by the proposed method and is therefore described in this chapter. Chapter 5, I was the co-author in which I applied the proposed method to predict dynamic performance characteristics. Only the sections with my personal contribution are included in this thesis to analyze the performance of the proposed method described in this thesis.

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|  |  |  |
| --- | --- | --- |
| Thesis Chapter | Publication title/full citation | Publication status |
| *Chapter 2* | A. Fatima, **T. Stachl**, M. S. Toulabi; W. Li, J. Tjong, G. Byczynski, and N. C. Kar, "Permeance–Based Equivalent Circuit Modeling of Induction Machines Considering Leakage Reactances and Non–Linearities for Steady–State Performance Prediction," *IECON 2021–47th Annual Conference of the IEEE Industrial Electronics Society*, 2021, pp. 1-6. | *Published* |
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# ABSTRACT

New electric vehicles demand higher performing, more cost-effective electric motors leading to the tractive induction motor (IM) being a promising choice for electric vehicles. Tractive IMs, however, have lower torque densities and slightly lower efficiency due to losses incurred in the rotor must be improved through rotor bar optimization to improve torque and reduced losses considering dynamic operating conditions. Numerous design factors, material limitations and performance characteristics must be considered during the design of tractive IMs prompting the use of optimization algorithms capable of systematically optimizing multiple design aspects. Unfortunately, conventional optimization algorithms are time consuming, limited objectives and input variables and susceptible to function bias resulting in undesirable traits for IM optimization. Therefore, a novel, robust non-dominated adaptive restart genetic algorithm capable of geometric rotor bar optimization considering dynamic operation is developed and proposed. To attain the desired optimization algorithm and optimal rotor bar geometry, this thesis: (1) Analyzes the challenges of IM design optimization, identifying optimization targets and design constraints. (2) Investigates and selects an optimization algorithm fit for IM design applications. (3) Proposes novel hyperbolic tangent based objective functions ensuring non-dominated solution. (4) A new adaptive restart genetic algorithm is developed with enhanced resistance to stalling minimizing run time. (5) The novel algorithm is implemented to optimize the torque and losses producing an optimal rotor bar which is validated and compared to a baseline IM. The proposed method is applicable to various IM topologies for multiple objective targets.

# DEDICATION

This thesis is dedicated to my other half, Miranda, and my family, Mara, Sonja, Chris and Tala. I love you all very much. Thank you for all your understanding, motivation, strength and support along the way. I would not have made it to where I am now without all of you.

To my friends who never failed to brighten my day, thank you gators. I appreciate and love you all. $20 to the first one of you to read it cover to cover!

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I would also like to thank all current and past members of the CHARGE Labs for your comradery throughout my time at the University of Windsor. I have learned from each of you. A special thank you to Dr. Aida Mollaeian for granting me access to the motor she designed and prototyped for use as the baseline motor in this thesis and to Dr. Shruthi Mukundan and Dr. Himavarsha Dhulipati for their warm welcome and patience when I entered the CHARGE Labs. Animesh Anik, Pengzhao Song, Areej Fatima and Buddhika G. Vidanalage, I greatly appreciate all your support and the friendship that was established. Lastly, I would like to thank a dear friend who I had the pleasure of sharing many laughs with, David Montgomery. Thanks, Buddy.

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# LIST OF ABBREVIATIONS

|  |  |
| --- | --- |
| **Abbreviation** | **Description** |
| LEM | Linear Electric Motor |
| REM | Rotary Electric Motor |
| LIM | Linear Induction Motor |
| LSM | Linear Synchronous Motor |
| HAM | Hybrid Analytical Model |
| HM | Harmonic Model |
| MEC | Magnetic Equivalent Circuit |
| ECM | Equivalent Circuit Model |
| FEA | Finite Element Analysis |
| OA | Optimization Algorithm |
| EA | Evolutionary Algorithm |
| NN | Neural Network |
| PSO | Particle Swarm Optimization |
| OMOPSO | Optimized Multi-Objective Particle Swarm Optimization |
| GA | Genetic Algorithm |
| NSGAII | Non-Dominated Sorting Genetic Algorithm II |
|  |  |
|  |  |
|  |  |
|  |  |

# NOMENCLATURE

|  |  |
| --- | --- |
| **Variable** | **Description** |
|  | Number of slots |
|  | Number of poles |
|  | Number of phases |
|  | Synchronous velocity |
|  | Electrical frequency |
|  | Pole pitch |
|  | Peak current |
|  | Phase current |
|  | Number of turns per coil |
|  | Magnetomotive force scaling factor |
|  | Number of nodes in the x-direction for a single coil |
|  | Slots/poles/phase |
|  | Conductivity |
|  | Vacuum permeability |
|  | Relative permeability |
|  | Slot height |
|  | Yoke height |
|  | Tooth width |
|  | Slot width |
|  | Slot pitch |
|  | Airgap |
|  | Aluminum thickness |
|  | Back iron thickness |
|  | Primary length |
|  | Primary height |
|  | Primary depth |
|  | Periodical length of model |
|  | Space harmonic |
|  | Spatial frequency for nth space harmonic |
| , | Complex harmonic analysis unknowns for nth space harmonic |
|  | Spatial position in the x-direction |
|  | Spatial position in the y-direction |
|  | Number of harmonic model regions in the model |
|  | Number of magnetic equivalent circuit regions in the model |
|  | y-index of a node in the magnetic equivalent circuit region |
|  | x-index of a node in the magnetic equivalent circuit region |
|  | Number of rows in a magnetic equivalent circuit region |
|  | Number of columns in a magnetic equivalent circuit region |
|  | Total nodes in a magnetic equivalent circuit region |
|  | Reluctance |
|  | Magnetomotive force |
|  | Flux |
|  | Complex scalar potential |
|  | Surface Area |
|  | Magnetic flux density |
|  | Magnetic field |

# Introduction

## Electric Vehicles–A Green Form of Personal Transportation

### A Surging Interest in Electric Vehicles

### Industry Leading Electric Drive System for Tractive Applications

## State of the Art Electric Motors for Tractive Applications

## Literature Survey on Traction Induction Motor Design and Geometry

### Stator Design and Geometry

### Rotor Design and Geometry

### Summary of the Effect of Geometry on Design Factors

## Induction Motor Optimization

### Tractive Induction Motor Analytical Modeling for Optimization

A model optimization algorithm must be chosen methodically and implemented effectively. Although it is possible to calculate the objective function for the entire search space to determine global maxima and minima, this is often computationally intensive and not a modular solution. Instead, an optimization algorithm can be implemented to calculate the objective function until convergence on a solution. To categorize the field of optimization algorithms, some classifications were provided to simplify the choice.

Diagram

Description automatically generated

Fig. 2.1. Classification of common optimization algorithms constrained to gradient-based and metaheuristic algorithms.

There are 3 main types of optimization algorithms shown in Figure X which serve a similar purpose in the optimization process. The evolutionary algorithm [EA] and the neural network [NN] are both metaheuristics while gradient-based algorithms [GBA] require function evaluations to determine search directions. Due to the limitations in complexity and flexibility, GBAs are used for small-scale or local optimizations. The model proposed in this paper requires metaheuristics, therefore the choice is limited to EAs and NNs. Although NNs are very effective at solving and predicting solutions to complex problems, such as classification, they are computationally intensive. As a result, EAs were chosen as the appropriate optimization algorithm category which includes the genetic algorithm [GA] and particle swarm optimization [PSO], to name a few.

Diagram

Description automatically generated

Fig. 2.2. Layout of a generic optimization algorithm depicting its optimization loop, termination conditional, and objective function.

A generic EA optimization approach is visualized in Figure X, highlighting the optimization loop, and defining a generic means for terminating the optimization. These algorithms find a balance between flexibility and efficiency while maintaining robustness which makes them desirable for most optimization problems. It is important to note that although an optimization algorithm becomes more robust when the number of objective function evaluations per iteration are increased, it often adds redundant computations which can be avoided through careful tuning of the solver which will be discussed in this chapter.

### Induction Motor Optimization Input Variables and Objective Targets

## Research Motivations

### Vehicle Level Motivations

### Motor Level Motivations

### Algorithm Level Motivations

## Research Objectives

## Research Contribution and Deliverables

## Organization of Thesis

This thesis proposes a novel method of metaheuristic optimization of LIMs to improve the thrust-to-weight ratio. The major sections of this thesis are as follows:

1. Chapter 1 provides an overview of EVs, LEMs and the use of OAs in induction machine optimization, demonstrating the motivations, challenges and objectives associated with the proposed method from a vehicle level to the motor level and the incorporation of the algorithm level.
2. The baseline LIM considered for optimization is introduced in chapter 2, outlining the base rotor bar shape and the baseline torque and loss performance is determined. The modified permeance based equivalent circuit model used in the proposed method is described and validated, and the optimization algorithm to be used is selected.
3. A novel OF modeling strategy is proposed and tested in chapter 3 to ensure all function bias is eliminated between the torque and loss objectives during optimization. The elimination of function bias ensures a balanced optimal solution across all objectives.
4. The development of a robust adaptive restart GA is detailed in chapter 4 to improve the algorithms ability to resist stalling and early convergence, increase the final solution quality and reduce the overall run time through intelligent search space reduction.
5. Chapter 5 incorporates the effects of various dynamic operating conditions required by tractive IMs into the optimization process. These dynamic operating points are determined over the WLTP -3 drive cycle and reduced using the energy center of gravity method ensuring operating conditions of the highest energy consumption are represented.
6. Chapter 6 analyzes the optimized rotor bar shape and performance against the baseline motor and validates using FEA. The algorithm performance of the novel non-dominated adaptive restart GA is analyzed and discussed.
7. Chapter 7 summarizes the results generated through the proposed method and identifies the future scope of the proposed research and developed method in the area of IMs and algorithm-based IM optimization.

# Optimization Algorithm Selection

Within the scope of evolutionary algorithms, GA and PSO are the dominant algorithms when the problem demands robustness and performance. With the overarching objective of integrating the optimization algorithm with the HAM, the comparison between PSO and GA must be carefully considered to ensure that the chosen solver can meet the unique demand of having the HAM as its objective function. In this section the core functionality of each algorithm will be discussed and then compare them against one another in a case study to statistically determine the optimal solver for the problem.

## Genetic Algorithm

The GA is a kind of evolutionary algorithm that mimics the general concept of evolution. Natural selection is often mentioned in the context of evolution since it is the strong individuals that survive in each environment. Being the strongest is a generalization that is defined by the objective function applied to the optimization problem. The structure of a population subject to the GA is visualized in Figure X encapsulating a fixed number of chromosomes, which themselves encapsulate genes.

A screenshot of a video game

Description automatically generated with medium confidence

Fig. 2.3. Layout of a genetic algorithm with an arbitrary number of chromosomes and genes per population.

To understand the function of a gene, the application of the algorithm must be defined since the genes are merely input variables to the model that requires solving. If the optimization problem were a 2-dimensional surface plot minimization, the inputs to the model would be an arbitrary 2-dimension coordinate. Each dimension of this coordinate is considered a gene through the nomenclature of the GA.

Diagram

Description automatically generated

Fig. 2.3. Layout of a genetic algorithm execution loop.

Throughout each iteration of the solver a new population is produced through the means of selection, crossover, and mutation. This iterative loop ensures that the algorithm favors the desirable solutions while maintaining robustness through some degree of randomized search throughout the optimization domain.

## Particle Swarm Optimization

Like GA, the PSO mimics the natural phenomenon of the power of a collective. This is often seen in swarms of insects such as bees which constantly communicate with one another to determine the optimal direction of the entire swarm. If the swarm’s objective were to find a new location to establish a hive, each bee plays a critical role to gather information and relay it throughout the swarm so that the collective can weigh the signals and converge on decisions in real time. Instead of the population, chromosomes, genes, and offspring terminology, the PSO uses swarm size, particles, and leaders.

Diagram

Description automatically generated

Fig. 1.4. Layout of a particle swarm optimization algorithm optimization loop.

The optimization loop of the PSO shows the process of updating velocities and positions per particle in the swarm as elaborated in equations X and Y.

(1)

(2)

The current and successive iterations are denoted as and respectively, where the local and global best solutions are determined prior to updating positions and velocities . The inertial weight coefficient, local weight coefficients and , and global weight coefficients and are integral in determining the relative influence the swarm has on the particle and vice versa.

|  |  |
| --- | --- |
| **Constant** | **Range** |
| **R** |  |
| **C** |  |
| **W** |  |

Referring to the optimization loop, the final step before calculating the objective function on the updated particles is to subject each particle to a mutation algorithm with a designated probability that the mutation executes. This allows for variation of the swarm and increasing the robustness of the solver to avoid convergence on local minima and maxima.

## Schwefel Function Minimization Case Study

A case study was conducted to determine the optimal optimization algorithm among the subset of EAs through the Schwefel test function. A test function is used to test the ability of an optimization algorithm to converge on a solution that is the global maximum or minimum rather than the function’s local maxima or minima. The Schwefel function was chosen since it has a plethora of local maxima and minima which can stall solvers prior to converging on the solution. The function is defined as:

where is the number of input dimensions and is the function input per dimension . The global minimum is located at inside of the hypercube for all

Chart, surface chart

Description automatically generated

Fig. 1.4. Surface plot of the Schwefel function on the input range.

Background pattern

Description automatically generated

Fig. 1.5. Contour plot of the Schwefel function on the input range highlighting the global minimum with a red cross.

To couple a solver to this test function, a new input is generated by the solver per iteration. These inputs are used to calculate and minimize the objective value through the Schwefel function until convergence on a solution. To ensure that each optimization algorithm is fairly compared in this case study, common solver parameters are used to configure each algorithm. Every algorithm will iterate over its population or swarm with the only solver termination criteria being the max number of stall iterations reached. Other solver termination criteria like reaching objective tolerance, timeout, and maximum iterations were omitted in this case study to isolate each solver through a consistent test domain. Additionally, the optimization process is conducted 5 times per algorithm to determine the average performance to ensure that an outlier does not significantly impact the decision making. Table X compares the EAs: PSO and GA through performance parameters like execution time and error. The solver accuracy is the principal performance parameter, while the solver time holds less value as a performance parameter. From these criteria, the PSO algorithm outperforms the GA in both solution accuracy and solver speed.

Table 1.2

Optimization Algorithm Configuration

|  |  |  |
| --- | --- | --- |
| **Algorithm** | **PSO** | **GA** |
| **Population/Swarm Size** | 200 | |
| **Offspring/Leader Size** |  | |
| **Algorithm Stall Iterations** | 30 | |
| **Global Upper Bound** | [500, 500] | |
| **Global Lower Bound** | [-500, -500] | |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **PSO** | **OMOPSO** | **GA** | **NSGAII** |
| **Average Time (s)** | 1.68 | 2.45 | 2.03 | 2.95 |
| **Average Error In X** | 0.0000 | 0.0000 | 0.0041 | 0.0039 |
| **Average Error In Y** | 0.0000 | 0.0000 | 0.0216 | 0.0009 |
| **Average Error in Objective** | 0.0000 | 0.0000 | 0.0001 | 0.0000 |

I should do another test similar to above but with function tolerance to expand on the robustness between models. This will give me at least another page of content

I SHOULD CREATE A TABLE COMPARING DIFFERENT CROSSOVERS USING

The EA chosen from this case study will be implemented to optimize the HAM which will require multi-objective optimization. Without modification, PSO and GA cannot optimize multi-objective problems and require a modified implementation that produces non-dominated solutions. The non-dominated sorting genetic algorithm II [NSGAII] is a modified implementation of the GA, while the optimized multi-objective particle swarm optimization [OMOPSO] is a modified implementation of the PSO. These algorithms were included in the comparison of Table X. The data is not in favor of the NSGAII algorithm, solidifying the decision to use OMOPSO as the multi-objective optimization algorithm for the HAM. This decision is further enforced through a comparative study between NSGAII and OMOPSO [Reference that OMOPSO is better than NSGAII](https://www.researchgate.net/publication/224212508_An_Experimental_Comparison_of_Multiobjective_Algorithms_NSGA-II_and_OMOPSO) which concludes that “The binary values of the metrics indicate that OMOPSO is relatively better than the NSGAII in two test functions and better in one test function”. As a result, all future optimization of HAM will be conducted using OMOPSO to gather non-dominated solutions for the motor optimization objective. THIS MEANS I NOW CANNOT REFER TO IT AS POPULATION AND NEED TO REFER TO IT AS A SWARM

Table 2.4

Optimization Algorithm Parameters

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| PS Optimization | | PSO | | GA Optimization | |
| Parameter | **Value** | **Parameter** | **Value** | **Parameter** | **Value** |
| Maximum Iterations | 25 | **Maximum Iterations** | 500 | **Maximum Iterations** | 500 |
| Max Stall Iterations | 5 | **Max Stall Iterations** | 25 | **Max Stall Iterations** | 25 |
| Function Tolerance | 10-6 | **Function Tolerance** | 10-6 | **Function Tolerance** | 10-6 |
| Global Upper Bound | [500, 500] | **Global Upper Bound** | [500, 500] | **Global Upper Bound** | [500, 500] |
| Global Lower Bound | [-500, -500] | **Global Lower Bound** | [-500, -500] | **Global Lower Bound** | [-500, -500] |
| Reduction Factor | 25% | **Swarm Size** | 200 | **Population Size** | 200 |
| Resolution | 100 | **Global Vector Constant** | 40% | **Crossover Fraction** | 30% |
| Resolution Factor | 15% | **Local Vector Constant** | 25% | **Mutation Fraction** | 10% |

Table 2.5

Optimization Algorithm Performance

|  |  |  |  |
| --- | --- | --- | --- |
| Optimization Algorithm | PS | PSO | GA |
| Total Iterations | 13 | 52 | 39 |
| Algorithm Run Time | 1.4560s | 9.3813s | 7.4137s |
| X1 Solution | 420.9706 | 420.9687 | 420.9687 |
| X2 Solution | 420.9706 | 420.9687 | 420.9687 |
| Function Value at Solution | 2.633 x10-5 | 2.5455 x10-5 | 2.5455 x10-5 |
| Error In Solution | 0.002633% | 0.0025455% | 0.0025455% |

## Generational Selection and Variation Methods

There are many core functionalities that are required for an EA to successfully navigate a problem’s constrained space and optimize towards a solution. This is no simple task and a misconfiguration of just one core function can result in an instable solver. This section will refer to a current iteration’s population as parents and future iterations as children to abstract the information from the previous GA and PSO sections. The classification of EA core functionality can be segregated into selection of dominant parents and variation for searching the domain in a robust fashion.

### Selection

Selection is a core solver function that identifies the strongest parents among the population through comparison of performance. This identification process is achieved with a fitness function, which is application specific, coupled with a maximization or minimization definition. Since the population size must remain constant, the weakest parents are removed from the current population and discarded. The remaining parents are then subject to variation which will be discussed in the next section. There are many robust selection algorithms that will find the highest performing parents such as Roulette Wheel and Rank selection, although in this paper the focus will be on Tournament selection. The basic principle is that a sample of parents are selected to compete against one another in a tournament-style comparison of their objective values. The likelihood of a parent being selected is dependent on the selection pressure which is a probabilistic measure of a candidate’s likelihood of participation in a tournament. This parameter is an indicator of a

winner = random.choice(population)  
  
for \_ in range(self.tournament\_size-1):  
 candidate = random.choice(population)  
 flag = self.dominance.compare(winner, candidate)  
   
 if flag > 0:  
 winner = candidate

solvers ability to converge since higher selection pressure relates to a higher convergence rate.

A picture containing text, electronics

Description automatically generated

Fig. 2.2. Layout of a Tournament selection algorithm using arbitrary objective values to highlight the winning decision based on a minimization problem.

To determine the best configuration for the Tournament selection, experiment results across many configurations were tabulated in Table X, which optimized the Schwefel test function. The Schwefel test function is defined in section 2.4 and will have a consistent configuration throughout each test in the case study to isolate the effect of the Tournament selection configurations.

[link](https://towardsdatascience.com/introduction-to-genetic-algorithms-including-example-code-e396e98d8bf3)

[Good link for mutation and selection](https://www.fernandolobo.info/ec1920/lectures/GAs-2.pdf)

[Another Good Link For All EA Functionality](https://www.tutorialspoint.com/genetic_algorithms/genetic_algorithms_mutation.htm)

[I NEED TO IMPLEMENT THIS TO VISUALIZE PSO](https://machinelearningmastery.com/a-gentle-introduction-to-particle-swarm-optimization/)

### Variation

Like real life, the EAs have core functions that are appropriately named after events in the natural process of evolution. Crossover is one of these functions. It allows parents to exchange their qualities and produce children while the remaining qualities are subject to some form of randomized initialization. The number of variables that are subject to be overwritten is defined by a crossover point as visualized in Figure X. Note that the values of the variables were limited to binary for simplicity, but the true values can contain any format such as integers and real numbers. Since the crossover point determines the percentage of variables shared among parents, it is important to not choose too small or large of a ratio due to solver robustness. If a small percentage of variables from the parents were crossed over then the solver may become stuck in local minima or maxima rather than the desired global alternative. Alternatively, a large percentage of variables crossed over between parents will have large variations in the solution and can cause an instability in the solver.

Graphical user interface

Description automatically generated with low confidence

Fig. 2.3. Visualization of crossover between two parent variables to produce two child variables governed by the crossover point.

The frequency that the crossover is applied is also an important configuration consideration. This is defined as the probability that crossover will occur between parents and is integral in the solver’s robustness. Like the crossover point, if the probability of crossover is set too high then the parents will often share variables when producing children which is susceptible to finding local minima or maxima rather than the desired global alternative. Contrasting this with a low probability of crossover between parents and the solver may become unstable. This is due to the children’s variable initialization relying on some form of randomized initialization which will resist solver convergence.

Mutation is another important function of the EAs which is responsible for manipulating the values of randomly selected variables within a parent. The probability for mutating a parent’s variables shall remain low to maintain solver robustness rather than introducing instability. The general concept of mutation is visualized in Figure X, which highlights the variables that were randomly selected for mutation within the parent.

A screenshot of a cell phone

Description automatically generated with medium confidence

Fig. 2.4. Layout of a genetic algorithm with an arbitrary number of chromosomes and genes per population.

Note that the values of the variables were limited to binary for simplicity, but the true values can contain any format such as integers and real numbers.

# Modelling Methodology

Due to the size and complexity required to build a HAM it is important to simplify the model into smaller procedures. The image below highlights the state transitions made by the model to produce a pre-processed motor, solve the motor, and produce a processed motor model. The motor performance parameters are then used to compute the genetic algorithm objective function value and compare it to a desired solver tolerance. Prior to building a pre-processed motor, the genetic algorithm will provide a weighted input in the form of slots and poles in the primary of the motor. Converging towards solver tolerance with the objective function indicates that the resulting performance parameters are optimized for a given slot-pole ratio of a motor.

Diagram

Description automatically generated

For this paper the fitness function measures the performance metrics of the motor after having solved the mesh. The performance metric values are then either maximized, minimized, or centered around a bias. After the solver has produced many generations of the population, the resulting slot-pole ratio will produce a motor with fine-tuned performance. Some common performance parameters of a motor are shown in Figure X. Although there are more performance parameters that indicate other useful characteristics of the motor, the GA solver is not efficient in large multi-objective optimizations.

Diagram

Description automatically generated

Fig. 2.3. Layout of the motor optimization algorithm inputs and the resultant multi-objectives.

Optimizing for thrust, mass, and efficiency tunes this application to produce competitive motors. Since they are all relatively important performance parameters it is important that the solver produces pareto-optimal solutions, meaning the solution equally satisfies the fitness function criteria. A solution that is not pareto-optimal will still optimize every multi-objective variable but with an inequal emphasis. This information allows the solver to select the strongest chromosomes among the group which will then be subject to crossover to exchange their advancement towards solver convergence with their child chromosomes.

## Significance of Objective Function Modeling

## Conventional Objective Function Modeling

## Novel Hyperbolic Tangent Based Objective Functions

# Enhanced Solution Quality Multi-Objective Rotor Bar Optimization Through Adaptive Restart Capabilities

# Rotor Bar Optimization Considering Dynamic Operating Conditions Through Energy Center of Gravity Clustering

## Significance of Considering Dynamic Operating Conditions

## Core Loss Prediction Under Dynamic Operating Conditions

### Core Loss Prediction Using Adaptive Restart Genetic Algorithm

### Adaptive Restart Genetic Algorithm Performance

## Considering Dynamic Operation Through Drive Cycle Based Testing

### Electric Vehicle Dynamics Modeling

### Simulated Dynamic Operating Points Over WLTC Class 3 Drive Cycle

## Operating Point Reduction Through Energy Center of Gravity Method

## Optimization Considering Multiple Operating Points

# Tractive Induction Motor Rotor Bar Optimization Using a Novel Non-dominated Adaptive Restart Genetic Algorithm Considering Dynamic Operating Conditions

## Novel Adaptive Restart Genetic Algorithm Performance

## Comparison of Optimal Rotor Bar Geometry and Validation

# Research Summary

## Conclusions

## Future Research on Rotor Bar Optimization of Tractive IMs

# REFERENCES

[1] “Total greenhouse gas emissions.” https://ourworldindata.org/grapher/total-ghg-emissions?tab=chart&country=~CAN (accessed Apr. 20, 2022).

# VITA AUCTORIS

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