

Electric Machine Design for Vehicle Powertrains Using Bayesian Optimization

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This paper proposes a framework for the optimization of electric vehicle (EV) powertrains utilizing physics-based electromagnetic models for the estimation of traction electric machine (EM) performance. Specifically, the framework employs finite element modeling to parameterize the electric motor, the output of which is utilized in a quasi-static vehicle model to holistically optimize the EV powertrain for efficiency. The framework minimizes computation time of each optimization iteration. This framework enables investigation of EM design parameters from a system-level perspective, providing relations between vehicle performance and EM design parameters. The proposed framework is to be applied with a selection of optimization parameter sets, investigating the impact of EM design parameter inclusion.

Index Terms—Design Optimization, Electric vehicles, Finite element analysis, Internal permanent magnet machine

I. INTRODUCTION

In the rapidly growing market for EVs, competition forces manufacturers to innovate in terms of both cost reduction and performance improvements. The duality of this pursuit often leads to a trade-off that is difficult to solve outright, however system-level optimization prior to component-level design can contribute to improving system design. Due to the multi-physical complexity and interdependence of the components, designing components while accounting for system-level impact is complex. An example of this is how the EM design is impacted by the battery size through torque requirements, changing the EM efficiency, impacting the required battery capacity and its size. System-level optimization can be an effective method to deal with this complexity.

Widely applied optimization methods for design optimization of EMs, such as genetic algorithm [1] or particle swarm [2], rely on a high number of cost-function evaluations. This provides the optimum and evaluated solutions without any optimality or convergence guarantees. By applying Bayesian optimization (BO) to the system-level problem, the investigation can be extended beyond finding an optimum to detailing the implication of EM design parameters on system behavior, in addition to having guarantees on the regret bounds [3]. In the field of powertrain optimization, the models of the EM are often simplified to improve solving speed or obtain optimality guarantees [4]. This reduces model accuracy and makes investigation of EM design parameters impossible.

In this study, a framework is proposed to optimize a preliminary EM design and study the effects of design parameters on system level behavior, at minimal computational effort. The framework is applied to the

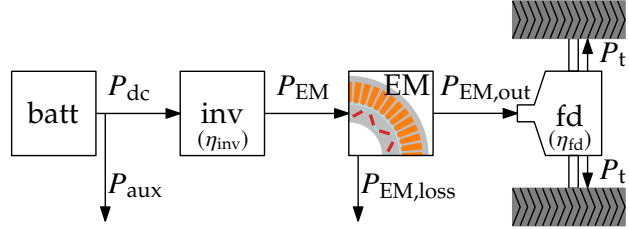


Fig. 1. A schematic of the electric powertrain consisting of the battery (batt), inverter (inv), electric machine (EM) and the final drive (fd).

optimization of a fixed-gear EV powertrain as shown in Fig. 1, optimizing the battery size, the final drive ratio and the EM design of an interior permanent magnet synchronous machine, focusing on the magnetic domain.

The organization of this paper is as follows: Section II details the proposed framework. A preview of the optimization of an EV powertrain is given in Section III, followed by the conclusion and outlook in Section IV.

II. OPTIMIZATION FRAMEWORK

To ensure that the optimizer can find a solution in a reasonable computation time, a framework architecture is required that employs component models in a time-efficient manner such that the powertrain's performance can be determined automatically. To this end, the architecture shown in Fig. 2 is used. The optimizer decides on candidate a set of optimization parameters called the probe: x_{probe} , the feasibility of which is checked against a set of constraints throughout the process, with failed constraints returning a high cost to the optimizer.

- The assessment starts by evaluating an analytical model to scale the machine geometry based on the probe and

an equivalent circuit model. If a solution can be found, the geometry is considered valid, and a 2D model of the EM is set-up inside the electromagnetic finite element model (FEM) software, for this paper Ansys Maxwell was used, where the geometric parameters and nonlinear material properties are applied. For the magnets, $\mu_r = 1.03$ and $H_c = -92\text{kA/m}$.

- In the electromagnetic FEM software, first, a complete electrical cycle is analyzed to determine whether the torque ripple complies with the constraint. If it does, a set of operating points is evaluated. For each operating point, the flux linkage ψ_{abc} and the magnetic field density $\vec{B}_{xy}$ are exported.
- This data is then processed to estimate the EM losses, determine the torque generation and the electromotive force generated by the EM. This information is then used to create an efficiency map by applying loss minimization control in combination with flux weakening.
- The estimated efficiency is used by a quasi-static vehicle model simulation with time step Δt to determine the energy consumption of the proposed powertrain, and vehicle requirement conformity.
- If the design complies with all constraints, the energy consumption is returned to the BO algorithm to determine a new probe according to a utility function.

This process will run continuously, with the optimizer determining a new x_{probe} for every iteration until the maximum number of iterations is reached.

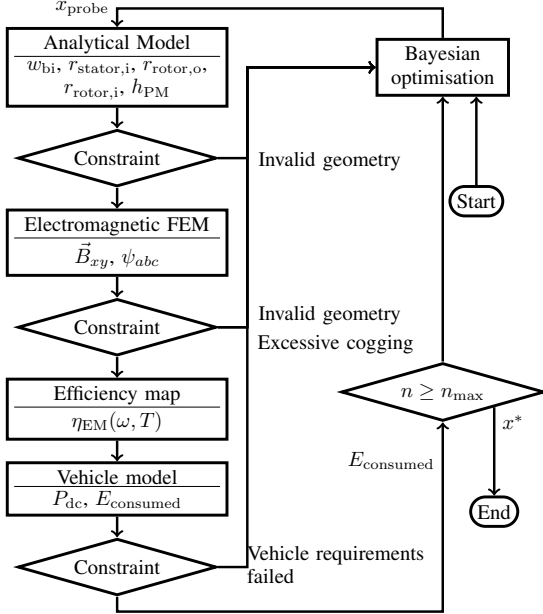


Fig. 2. Schematic overview of the optimization framework. n : The number of iterations, x^* : The optimal selection of the decision variables.

III. DESIGN PARAMETER SENSITIVITY

Part of the results of a three-dimensional optimization containing only EM design parameters are given in

Fig. 3, specifically the relation between the EV energy consumption and width of the permanent magnet. It is clear from both the probes and cost-function estimation that there is only a specific region in which the permanent magnet (PM) width returns a valid design, as the cost for breaking a constraint is set at 230 Wh/km. While the estimate of the BO optimizer could be likely be improved with further tuning of the kernel. It clearly identifies this entire valid region, in addition to trends relating the design parameter with system performance.

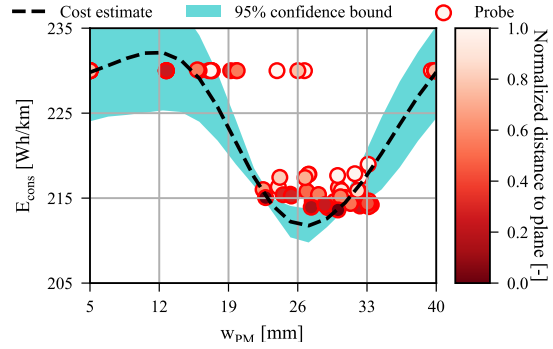


Fig. 3. Bayesian approximation of EV energy consumption as a function of the width of the PM. The three-dimensional problem is projected onto a single dimension, with the remaining optimization parameters fixed at their optimal value. The distance of the probe to the plotted plane is represented by the red gradient.

IV. CONCLUSION AND FUTURE WORK

In this paper, a framework is proposed for the optimization of EM design in the scope of EV powertrains. By implementing BO in combination with FEM analysis into holistic powertrain optimization, it becomes possible to find the optimum design and analyze the relations between design parameters and the system behavior. The framework presented in this paper has been applied to a variety of optimization parameter sets to study the impact of including EM internal design parameters on powertrain optimization and evaluate the feasibility of the proposed framework on larger optimization sets. These results will be presented in the full version of this paper.

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