# **System Level Multi-objective Optimization Method for Electrical Drive Systems**

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**Industrial applications of electrical machines and their drive systems often involve simultaneous design and optimization of multiple objectives that usually contradict to each other. This work aims to present system-level deterministic and robust design methods for the multi-objective optimization of electrical drive systems. Two approximation techniques, Kriging model and Taylor approximation are presented to improve the optimization efficiency. Thereafter, an electrical drive system consisting of a permanent magnet transverse flux machine and a field oriented control scheme is investigated to illustrate the performance of the proposed method. Deterministic design and robust optimal Pareto solutions are presented and discussed for the multi-objective optimizations, respectively. It can be seen that the robust multi-objective optimization can produce optimal Pareto solutions with smaller standard deviations for design requirements than the deterministic approach for this drive system. More importantly, the failure probability of the drive system can be reduced significantly by using the robust multi-objective optimization.**

*Index Terms***—Electrical machines, motor drives, optimization methods, robustness.**

### I. INTRODUCTION

PTIMIZATION design of electrical drive systems often **OPTIMIZATION** design of electrical drive systems often involves multiple objectives for both motors and control systems, such as motor cost and efficiency, and speed overshoot and torque ripple. Thus, the corresponding design and optimization are actually multi-objective issues [1]-[3].

 Regarding the multi-objective optimization of drive systems, most of the current works focus on the motors only, such as high efficiency and/or low torque ripple [4], [5]. However, they are on the component level, i.e. motor level, rather than on system level as the design parameters in control systems have not been considered. Therefore, the system's performance, especially the dynamic performance cannot be ensured. On the other hand, the real quality of motors and drives in mass production highly depends on the available machinery technology and those unavoidable variations or uncertainties in the manufacturing process, and assembly process. Traditional deterministic design optimization method cannot handle these variations. This is the main reason why robust optimization is popular nowadays [6], [7]. **L.** INTRODUCTION min:  $[f(x), ..., f_y(x)]$ <br> **C.** FINITE CONFIGURE TO THE TRANSFER CON MOTORS and the distance of the form as the form as min in the form as the form as minimized of the main and opinization are actually multi-objec

 Optimization efficiency issue becomes critical for electrical drive systems with the introduction of robust optimization. The most computational burden is from finite element analysis (FEA) of motors, simulation calls of controllers, Monte Carlo analysis (MCA) of the robust analysis. This work aims to present system-level deterministic and robust design methods for the multi-objective optimization of drive systems.

# II.MULTI-OBJECTIVE OPTIMIZATION MODELS FOR ELECTRICAL DRIVE SYSTEMS

Fig. 1 illustrates a brief system-level design and optimization framework for electrical drive systems. As shown, there are many design parameters (including motor design parameters and control parameters), objectives and constraints. In general, a multi-objective deterministic design model with respect to *p* objectives  $f(\mathbf{x})$  and *m* constraints  $g(\mathbf{x})$ 

$$
\min: \quad [f_1(\mathbf{x}), \dots, f_p(\mathbf{x})] \n\text{s.t.} \quad g_i(\mathbf{x}) \le 0, \ i = 1, \dots, m ,\n\mathbf{x}_i \le \mathbf{x} \le \mathbf{x}_u
$$
\n(1)

where  $\mathbf{x}_l$  and  $\mathbf{x}_u$  are the boundaries of the design parameter  $\mathbf{x}$ , To consider the manufacturing variations, model (1) can be converted into a robust design model (2) based on a technique

called design for six-sigma (DFSS).  
\nmin: 
$$
\left[ F_1(\mu_{f_1}(\mathbf{x}), \sigma_{f_1}(\mathbf{x})), ..., F_p(\mu_{f_p}(\mathbf{x}), \sigma_{f_p}(\mathbf{x})) \right]
$$
  
\n  
\ns.t.  $\begin{cases} g_i(\mu_f(\mathbf{x}), \sigma_f(\mathbf{x})) \le 0, i = 1,...,m \\ \mathbf{x}_t + n\sigma_{\mathbf{x}} \le \mu_{\mathbf{x}} \le \mathbf{x}_u - n\sigma_{\mathbf{x}} \\ LSL \le \mu_f \pm n\sigma_f \le \text{USL} \end{cases}$ , (2)

where  $\mu$  and  $\sigma$  are means and standard deviations, *n* is the sigma level. In the implementation, MCA is usually employed to evaluate the quality indicators  $\mu$  and  $\sigma$  [1], [6]. In order to improve the optimization efficiency, Kriging model is used to reduce the computation cost of FEA, and Taylor approximation is employed to decrease the controller simulation cost used in MCA.



Fig. 1. System level design and optimization framework for drive systems

## III. EXAMPLE STUDY

A drive system consisting of a transverse flux machine (TFM) as shown in Fig. 2 [1]-[3] and a field-oriented control (FOC) system as shown in Fig. 3 will be investigated in this section. In the optimization, seven motor structural parameters and two PI control parameters are selected as the optimization parameters of the whole drive system. The multi-objective

parameters of the whole drive system. The multi-objective optimization model of this drive system is defined as  
\n
$$
\min: \begin{cases} f_1(\mathbf{x}) = \text{Cost}(PM) + \text{Cost}(Cu) \\ f_2(\mathbf{x}) = -T \end{cases}
$$
\n
$$
\text{s.t.} \begin{cases} g_1(\mathbf{x}) = 0.795 - \eta \le 0, \ g_2(\mathbf{x}) = 640 - P_{\text{out}} \le 0, \\ g_3(\mathbf{x}) = sf - 0.8 \le 0, \ g_4(\mathbf{x}) = J_c - 6 \le 0, \\ g_5(\mathbf{x}) = \text{RMSE}(T) - 0.06 \le 0, \ g_6(\mathbf{x}) = \text{RMSE}(\omega) - 0.03 \le 0 \end{cases}
$$

 $\mathbf{I}$ 

where  $f_1$  is the material cost,  $f_2$  the torque output.  $\eta$  and  $P_{\text{out}}$ are the motor's efficiency and output power respectively, *sf* and  $J_c$  the fill factor and current density of the winding, respectively.  $\omega$  is the dynamic response of speed.

 Figs. 4-6 and Table I show the optimization results. The following conclusions can be drawn from them.

 1) As shown in Fig.4, the front of the Pareto solutions obtained from robust multi-objective approach is obviously lower than the deterministic approach. It means that the needed cost of robust design is higher than that of deterministic design to achieve the same torque for this drive system. However, as shown in Fig.5, the probability of failure (POF) of optimal Pareto points from deterministic multiobjective design are unstable and obviously higher than those from robust design. These are very bad design schemes from the point of view of industrial quality designs.

 2) As shown in Fig. 6 and Table I, constraints in robust multi-objective approach have smaller standard deviations and better means (such as bigger efficiency and smaller current density) than in the deterministic approach, which means robust multi-objective approach can produce more highquality products than a deterministic approach.

 In brief, the reliabilities and sigma levels obtained from robust multi-objective approach are obviously better than those from the deterministic approach. Therefore, system-level robust multi-objective design optimization is necessary for the modern quality design of industrial electrical drive systems.



Fig. 2. Prototype of a TFM, (left) rotor, (right) 3 stack stator



Fig.3. FOC scheme for the PM TFM



Fig. 4. Pareto solutions for the drive system



Fig. 5. POF values for optimal Pareto points



Fig. 6. Mean of current density for all Pareto points

TABLE I MEAN OF THE CONSTRAINTS

Constrains	Deterministic		Robust	
	μ	σ	μ	σ
η	0.818	0.001	0.826	0.001
$J_c$	5.88	0.11	5.32	0.09
RMSE(T)	0.019	0.006	0.017	0.003
$RMSE(\omega)$	0.005	0.0125	0.001	0.0001

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