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System Level Design Optimization Methods for Electrical Drive Systems – Deterministic Approach

*Abstract*—Electrical drive systems are key components in modern appliances, industry equipment and systems, e.g. hybrid electric vehicles. To obtain the best performance of these drive systems, the motors and their control systems should be designed and optimized at the system level rather than the component level. This paper presents an effort to develop system level design and optimization methods for electrical drive systems. Two system level design optimization methods are presented in this work, namely single level method (only at system level) and multilevel method. Meanwhile, approximate models, design of experiments technique and sequential subspace optimization method are presented to improve the optimization efficiency. Finally, a drive system consisting of a permanent magnet transverse flux machine with soft magnetic composite core is investigated, and detailed results are presented and discussed. This is a high-dimensional optimization problem with 14 parameters mixed with both discrete and continuous variables. The finite element analysis model and method are verified by the experimental results on the motor prototype. From the discussion, it can be found that the proposed multilevel method can increase the performance of the whole drive system, such as bigger output power and lower material cost, and decrease the computation cost significantly compared with those of single level design optimization method.

*Index Terms*— Approximate models, finite element methods, model predictive control, multilevel design optimization, transverse flux machine, system level design optimization.

# INTRODUCTION

E

LECTRICAL machines and the corresponding drive systems have a history of over a century and the design procedure has become almost “standard”. When designing an appliance that needs an electrical drive system, the designer firstly selects the motor, inverter/converter and controller from the existing products. The appliance designer, on one hand, has to deliver the functions that the appliance is supposed to have; and on the other hand, has to take into account the availability and performance that the existing motor drive can provide. This motor manufacturer-orientedapproach has been the dominant design concept for drive systems for a long time. However, this approach would apply many constraints to the design and therefore limit the functions of the appliance.

With the fast development of CAD/CAE software, new material, flexible mechanical manufacturing technology, advanced optimization and control algorithms, it is possible to design a motor to meet the special requirements of a particular application. Since the early 1990s, this application orientedapproach has become a common practice. Nowadays, the motors and their control systems are generally closely integrated into the appliances. Therefore, more and more holistic integrated design problems of the electrical drive systems, especially novel electrical drive systems, have boomed in industry.

The electric vehicles and hybrid electric vehicles are good examples, which are attracting great attentions and funding from the governments and general public around the world because of the worldwide fossil fuel energy crisis and severe greenhouse gas emissions of the conventional vehicles powered by the internal combustion engines. To improve the efficiency and drive performance with reduced volume, weight, and cost of novel drive systems to meet the challenging requirements of hybrid electric vehicles, a great amount of recent efforts are being directed towards the development and optimum design of high performance drive systems for (plug-in) hybrid electric vehicles [1]-[3].

Through the extensive research practice, it is recognized that when designing such an electrical drive system, it is important to pursue the optimal system performance rather than the optimal components like motor, because assembling individually optimized components into a system cannot necessarily guarantee an optimal system performance. The optimal system performance can only be achieved through a holistic approach of integrated optimization of all components at the system level.



Fig. 1. Multi-domain design framework for electrical drive systems

Fig. 1 shows a classic design framework and the coupled relations for electrical drive systems. From this diagram, it can be seen that design optimization of such a drive system is really a multi-domain problem which includes electromagnetic, material, mechanical, thermal and power electronic designs and they are strongly coupled. In order to achieve high system level performance, the perfect cooperation of motor and its drive and control systems must be investigated synchronously.

Although the importance of system level design optimization of drive systems is noted, not much work has been reported in the literature [4], [5].Traditional design and optimization methods are mostly on the component level of motors, such as different kinds of motors [6]-[12]. Generally, cogging torque, torque ripple, cost, weight and energy consumption are the main concerns for motors’ performance parameters in the design and optimization process [13]-[15].

For the design optimization of these motors, the first step is to build analysis models for their performance parameters. There are at least two kinds of analysis models, analytical model [6], [8], [16], [17] and finite element model (FEM) [11]-[13], [17]. The second step is to optimize these models. Generally speaking, two kinds of optimization methods have been developed and widely employed to seek for the optimal performance of these motors. The first one is different types of numerical optimization algorithms, such as conjugate gradient algorithm, sequential quadratic programing algorithm [8] and intelligent optimization algorithms. Several intelligent optimization algorithms, such as genetic algorithm (GA) [18]-[20], differential evolution algorithm (DEA) [21] and particle swarm optimization (PSO) algorithm [22], [23] have been widely used to find the global optimal solutions for those motors. The second one is different types of approximate models, such as response surface model (RSM), radial basis function model, Kriging model and artificial neural network model. They are generally used to replace the FEM analysis of motors so as to reduce the FEM computation costs [5], [24].

On the other hand, for the controller part, though a lot of control algorithms have been developed, such as field oriented control (FOC), direct torque control (DTC) and model predictive control (MPC) [25]-[29], they are also generally designed and optimized on the controller level, and have not been combined with the design optimization of motors [30].

This component-level-based method may be reasonable for some traditional motors and their drive systems where there is much design experience that can be used. However, there is not much design experience for novel electrical drive systems. Furthermore, these methods are not system level holistic design basically. As previously discussed, by this component level approach, one can hardly achieve the optimal system performance. Therefore, how to design and optimize novel high performance drive systems is an important problem in both research community and industrial applications.

In order to deal with the above problems, this work presents an effort to develop system level design optimization methods for electrical drive systems under deterministic design approach. Deterministic approach means that noise factors of the design parameters will not be investigated in this paper. This paper is structured as follows. Section II presents system level design optimization framework, model and a single level (only at the system level) optimization method for electrical drive systems. Section III presents multilevel design optimization methods for drive systems. Meanwhile, several techniques aiming to improve the optimization efficiency are also presented in this section. Section IV describes the investigated drive system. Section V presents the performance of the proposed design optimization methods followed by the conclusion section.



Fig. 2. System level design optimization framework for drive systems

# System Level Design Optimization Method

## System level design optimization framework and model

Fig. 1 illustrates a multi-domain design framework for electrical drive systems. However, the design modules are strongly coupled and it is not easy to derive the design and optimization flowchart from this framework. Fig. 2 shows a deductive system level design and optimization framework for electrical drive systems. It mainly includes five steps, namely system inputs, selection, design, optimization, and evaluation.

Step 1: Determination of system’s requirements and specifications. In this step, system’s objectives and constraints, such as cost, weight, torque ripple and motor efficiency have to be considered and defined.

Step 2: Selection or design of motor type, drive and controller type with respect to the system specifications. This step can be done by expert experience. As shown in Fig. 2, the drive system can be divided into two parts, namely motor and controller, and the latter one includes drives and control circuits. There are some interactions between these two parts, *e.g.* some types of controller fit the given types of motor better than the others.

Step 3: Design of motor and controller. For motor part, this step consists of electromagnetic design, material design, dimension design, mechanical design, thermal design, and so on [13]. For controller part, it mainly includes the design of control circuits and control algorithms.

Step 4: Construction of design optimization models for motor, controller and the whole system. For motor part, the design optimization model can be defined as

, (1)

where **x***m*, *fm* and *gm* are the design parameter vector, objectives and constraints of motor respectively, **x***ml*and **x***mu* are the lower boundary and upper boundary of **x***m* respectively, *Nm* is the number of the constraints. It should be noted that the objectives and constraints in (1) must be defined in terms of the required system’s objectives and constraints in step 1.

For control part, the design optimization model can be defined as

, (2)

where **x***c*, *fc* and *gc* are the design parameter vector, objectives and constraints of control part respectively, **x***cl* and **x***cu* are the lower boundary and upper boundary of **x***c* respectively, *Nc* is the number of the controller’s constraints. It should be noted that the objectives and constraints in (2) must also be defined with respect to the required system’s objectives and constraints.

With motor’s and controller’s design optimization models (1) and (2), the system level design optimization model of a drive system can be defined as (3).

, (3)

where , **x***sl* and **x***su* are the lower boundary and upper boundary of **x***s* respectively, *fs* is the system’s objective which is generally a function of *fm* and *fc*.

Step 5: Evaluation of system’s performance. This step consists of two parts. One is the evaluation of steady performance of motor, such as cost and efficiency. The other is the evaluation of dynamic performance of controller or the whole drive system, such as overshoot, settling time, torque ripple and speed ripple.

## System level optimization method

Fig. 3 illustrates an optimization method for electrical drive systems. It can be seen that the optimization process is only implemented at a single level for the whole system which is called as system level. This method mainly includes three steps.



Fig. 3. System level optimization method for electrical drive systems

Step 1: Determination of system level optimization model (3). It includes the selection of motor and controllers for a specific drive system.

Step 2: Selection of an optimization method for model (3). As drive systems are always high dimensional and non-linear design problems, intelligent algorithms, such as GA, DEA and PSO algorithms can be good choices in many situations. Therefore, the algorithm parameters should be determined in this step, such as genetic operators in GA.

Step 3: Implementation of optimization process. Firstly, generate initial population of **x***s*. Secondly, evaluate performance parameters of the drive system and the objectives and constraints in (3). Thirdly, implement the optimization algorithm until convergence criteria are met. Finally, terminate and output the optimal solutions.

It should be noted that all the design parameters are only considered at the system level for this optimization method, so this method can be also regarded as a single level optimization method for electrical drive systems.

However, the computation cost of this single level optimization method is always very huge as these design problems are generally high dimensional, nonlinear with strongly coupled multi-domain design and analysis. As different domains have different analysis techniques and software, the computation cost of whole system is very expensive. For example, power electronic circuit analysis is needed in the control part, but the needed characteristic parameters of motor are generally calculated from finite element model (FEM) in motor part, so the power electronic circuit design and electromagnetic design are strongly coupled in electrical drive systems. Furthermore, the computation cost of finite element analysis is usually very expensive too in many situations, especially for some three-dimensional flux complex structure motors. Therefore, to overcome these problems, we present the following multilevel design optimization method.



Fig. 4. Multilevel optimization framework for electrical drive systems

# Multilevel Design Optimization Method

## Multilevel design optimization framework

Fig. 4 shows a multilevel design optimization framework for electrical drive systems. Three levels are considered in this framework, namely motor level, control level and system level. This optimization method includes three steps as follows.

Step 1: Determination of optimization models (1) and (2) for motor level and control level respectively. It should be noted that all the required system’s objectives and constraints should be defined in (1) and (2), so that only two levels, motor level and control level, are needed to be optimized in this framework.

Step 2: Optimization. This step includes two optimization processes for motor level and control level respectively.

Motor level: the aim of this level is to optimize the motor model (1) and evaluate the steady performance of motor, such as cost, weight, output power and efficiency. Furthermore, motor characteristic parameters should also be calculated in this step, such as resistance, inductance and magnetic flux of winding for the design optimization of next control level.

Control level: the aim of this level is to optimize the control model (2) and evaluate the dynamic performance of whole system, such as overshoot and setting time.

Step 3: Verification of system level performance (3). The aim of this step is to evaluate system performance and output the optimization results.

## Improvement of optimization efficiency

As mentioned above, the design optimization of drive systems is always high dimensional, nonlinear with strongly coupled multi-domain design and analysis. Therefore, the optimization efficiency of multilevel optimization method mainly depends on two issues. The first one is how to construct an efficient multilevel optimization framework, especially for the high-dimensional problems. The second one is how to reduce the computation cost of optimization models.

Based on the above discussion, three effective ways based on our previous study are introduced to improve the optimization efficiency in this part. They are approximate models, design of experiments (DOE) technique and sequential subspace optimization method (SSOM). Approximate models are generally used to reduce the computation cost of optimization models or the FEM in motor’s electromagnetic design and analysis. DOE and SSOM are presented to construct efficient multilevel optimization framework.

### Approximate models

There are four kinds of approximate models which have been widely used in optimization design of electromagnetic devices, namely RSM, radial basis function (RBF) model, Kriging model, and artificial neural network (ANN) model [31]-[33]. RSM and RBF models are parametric models, Kriging is a semi-parametric model, and ANN model is non-parametric model. Kriging model will be investigated in this work.

Given *ns* sample points  and their responses , for an input **x**, the response value *y*(**x**) of Kriging model can be expressed as

 (4)

where  is a deterministic term for global modeling.  is a known approximation model, which is generally assumed as a polynomial and has the form as , where *q* is the dimension of polynomial; **β** is the model parameter vector to be estimated. *z*(**x**) is a random error term used for the modeling of local deviation. It is usually assumed to be a vector with mean of zero, variance *σ*2 and covariance matrix [*cij*] as

 (5)

where **R** is the correlation matrix, and *R* is the user-specified correlation function. Gaussian correlation functions are most commonly used. More details about Gaussian correlation functions and the estimation methods for the parameters in them can be found in refs. [34]-[37].

By using the best linear unbiased estimation in Statistics, the predictor of the and parameter **β can** be expressed as follows.

 (6)

 (7)

where **F**, *r*(**x**) and **y** are defined as

, (8)

, (9)

. (10)

Then by using the maximum-likelihood estimation method, the estimation of is

. (11)

Implementing a Kriging method consists of estimating the parameters **β** in (4), in (5) and the parameters in Gaussian correlation functions (5). All the parameters can be estimated by the software package DACE (Design and Analysis of Computer Experiments) [35]. Compared with the parameter model, e.g., RSM, Kriging model can include not only the mean trend term but also the variances of the responses, so it is claimed to be superior in the modeling of local nonlinearities and has been widely used in the optimization design of electromagnetic devices recently [33], [36]-[39].

### Design of Experiments (DOE) technique

The above models can be used to approximate models in (1) and (2) to reduce the optimization cost, or they can be also employed as the approximate models for FEMs in the motor optimization. However, it should be noted that they may be only accurate for some low dimensional problems. For the high dimensional problems, how to use them to achieve accurate models is still an open problem. To deal with this problem, a possible way is to classify the significant factors out of all design parameters and deal with them with priority. To determine the significant factors, DOE technique is generally needed.

DOE is a very important technique in engineering design. It can be used to efficiently sample points for the construction of above approximate models, such as full factor sampling method and orthogonal sampling method [40]. Meanwhile, for the high dimensional problems, it can be used to identify a design parameter which is significant to the objectives or not with some statistical analysis techniques, e.g., the analysis of variance.



Fig. 5. A flowchart of SSOM for motor level or control level

### Sequential subspace optimization method (SSOM)

As we have known, for a high dimensional design problem, some design parameters may be significant to the objectives but the others not. Therefore, the whole parameters space can be divided into two or three subspaces in terms of their significant orders, and then these subspaces can be optimized sequentially with respect to their significant orders. Following this idea, a SSOM was presented in our previous study for the optimization of electromagnetic devices [41]. Fig. 5 illustrates a flowchart of SSOM with three subspaces. It mainly consists of four steps.

Step 1: divide the initial design space into three subspaces. In this step, DOE technique or expert experience can be used to determine the significant order for each design factor. And then place it to one of the three subspaces X1, X2 and X3, which represent highly-significant factors subspace, significant factors subspace and non-significant factors subspace respectively. The determination process should be done for motor level and control level respectively. The number of subspaces is related to the dimension of the problem, and two subspaces may be reasonable for some situations, *e.g.,* the dimension is smaller than 10.

Step 2: Optimize the highly significant factors subspace X1. In the implementation, the initial parameters in X2 and X3 are fixed. The optimization method in this subspace may be approximate models, intelligent algorithms and sequential optimization method (SOM) [32], [42]. Basically, SOM can be regarded as a space-to-space optimization strategy compared with the point-to-point optimization strategy of traditional intelligent algorithms, such as GA and DEA. It consists of two optimization processes, namely coarse and fine optimization processes. The main aim of the former process is to reduce the design space to a small space in which the final optimal point is mostly located. The purpose of the latter process is to update the model in the local space and find the optimal solution.

Step 3: Optimize the significant factors subspace X2. In the implementation, the parameters in X1 are fixed at the solutions obtained from step 2.

Step 4: Optimize the non-significant factors subspace X3. In the implementation, the parameters in X1 and X2 are fixed at the solutions obtained from steps 2 and 3.

Step 5: Termination step. If objective meets specification, output the optimal solutions. Otherwise, update the parameters in X2 and X3 and go to step 2.

It should be noted that SSOM can be used for motor level and control level synchronously. Therefore, the multilevel design optimization framework can be extended by this method. For example, if the motor parameters can be divided into two subspaces and the control level can be divided into three sublevels, then a five-level optimization framework can be constructed finally.

## Remarks on multilevel design optimization method and sequential optimization methods

Some remarks on the comparisons between the proposed multilevel design optimization method and several sequential optimization strategies (SSOM, SOM, et al.) will be presented below. Firstly, the main difference between the multilevel design optimization method and SSOM is that the multilevel method is proposed for the framework design optimization of whole drive systems while the SSOM is introduced for the optimization of each part, such as motor part or control part. Secondly, there are several kinds of sequential optimization strategies which have been widely used in design optimization of electromagnetic devices, such as sequential quadratic programming (SQP) algorithm [43], sequential approximation model optimization, and SOM developed in our previous work [32], [42]. However, they have some drawbacks for the optimization of high dimensional motors involving the analysis FEM.

First of all, SQP algorithm generally needs the analytic equations of motors to implement this algorithm so as to get the optimal results. However, it is hard to get these equations from FEM models. Secondly, for sequential approximation model optimization and SOM, their first step is to sample FEM points to construct approximation models in the initial design space. These methods are applicable and efficient for low dimensional problems, but they are hard to handle with high dimensional problems. For example, if we consider a motor with 8 design parameters, and we use 5 level full factor DOE technique to generate the first sample set, we need to calculate 58=390625 FEM samples. This is not applicable for most motor design problems as it will result in huge FEM computation cost. Therefore, they can only be used for the optimization of each subspace/sublevel in SSOM as the subspaces (X1, X2, and X3) are usually low dimensional.

In summary, the multilevel method is a design and optimization framework for the whole drive systems. SSOM is the optimization strategy for each part of drive systems, such as motor or control. And classic sequential optimization methods, such as sequential approximation model optimization and SOM can be employed as the specific methods for the optimization of each subspace/sublevel in SSOM.

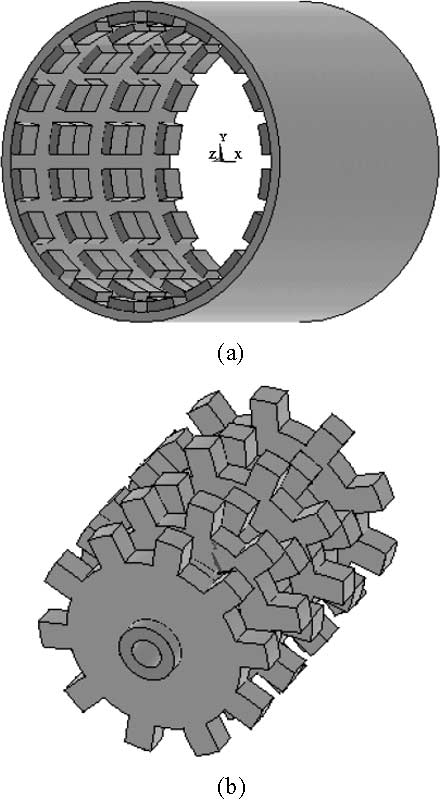
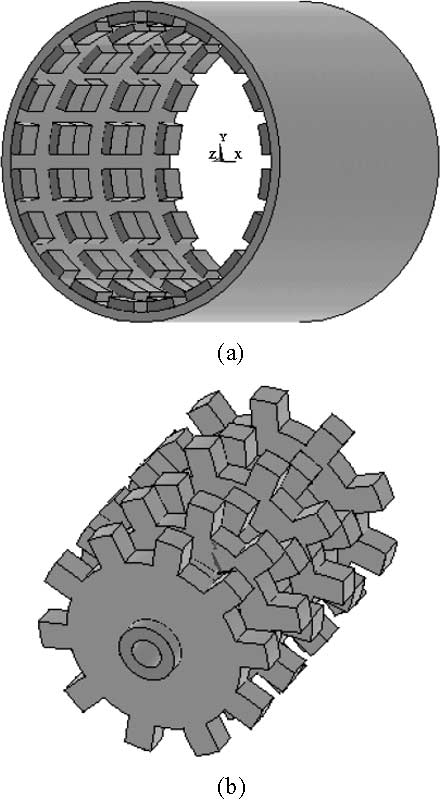
 

Fig. 6. Magnetically relevant parts of PM TFM: (a) rotor with PMs, (b) stator with SMC core

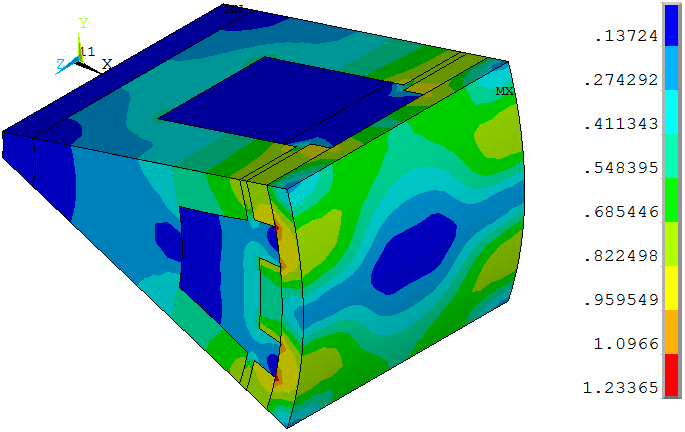


Fig. 7. Magnetic field analysis illustration for the PM TFM

# Description of a Drive System

Recently, the study of PM transverse flux machines (TFMs) and their application in direct drive systems have become a topic of much interest, especially the novel TFMs for the applications in hybrid electric vehicles, *e.g.*, in-wheel motors [44], [45]. In this example, we will investigate a drive system consisting of a PM TFM with a new material for the stator and an improved MPC control system.

## Design optimization model for motor level

This motor is designed to deliver a power of 640 W at 1800 r/min. The stator is designed by using a new material, soft magnetic composite (SMC) to replace the traditional silicon sheets. SMC has many unique advantages for this kind of machine, such as isotropic magnetic properties, low eddy current loss, cheap and easy to recycle. This machine has many advantages, *e.g.*, the armature carries significant magnetic field in all three directions so that the core material potential can be fully exploited [46], [47]. Therefore, it is a very promising motor for the direct drive systems. Fig. 6 shows the magnetically relevant parts of this machine, where stator cores are made by SMC material. Fig. 7 shows a 3D electromagnetic field analysis model for this machine which is obtained under no-load situation. Table I lists some design dimensions for this machine [48].

For the performance analysis of this machine, its power, torque and efficiency can be calculated by the following equations.

 (12)

 (13)

 (14)

 (15)

 (16)

where *P*out, *P*em, *P*Fe, *P*mec and *P*in are the output power, electromagnetic power, core loss, mechanical loss and input power respectively. *E*1 and *I*1 are the phase back emf and current in rms value. *ωr* is the rotational angular speed in mechanical rad/s and *k* is the motor back emf constant; *T*out and *η* are output torque and efficiency respectively. More details can be found in ref. [48].

TABLE I

Main Design and Optimization Parameters

|  |  |  |  |
| --- | --- | --- | --- |
| Description | Unit | Value | Opt. Par. |
| Number of phase | --- | 3 | --- |
| Number of poles | --- | 20 | --- |
| Number of stator teeth | --- | 60 | --- |
| Number of magnets | --- | 120 | --- |
| PM circumferential angle | deg | 12 | *xm*1 |
| PM width | mm | 9 | *xm*2 |
| SMC tooth circumferential width | mm | 9 | *xm*3 |
| SMC tooth axial width | mm | 8 | *xm*4 |
| SMC tooth radial height | mm | 10.5 | *xm*5 |
| Number of turns | --- | 125 | *xm*6 |
| Diameter of copper wire | mm | 1.25 | *xm*7 |
| Air gap length | mm | 1.0 | *xm*8 |

For the optimization of this machine, eight parameters are considered as the optimization variables as shown in Table I. From our design experience and previous work, it is found that these parameters are significant to the motor’s performance. All these parameters should be optimized to minimize the cost of material and/or maximize the output power of the motor. The objective cost mainly includes the material costs of PM, copper, SMC core and steel. Furthermore, four constraints are also considered for this machine. The optimization model can be defined as follows.

 (17)

where *w*1 and *w*2 are weight factors; *Cost*initial and *P*out\_initial are the cost and output power (*P*out) of the initial PM TFM developed in [48]; 0.795 and 640 are the rated values of efficiency (*η*) and output power respectively for the initial design; *sf* is the fill factor of the copper wire winding; and the last constraint is the current density (*Jc*) of the copper wire, which should be no more than 6 A/mm2 [5].

## Design optimization model for control level

Recently, MPC has been applied to drive PM synchronous machine (PMSM) to reach high performance of dynamic torque control [28], [29], [49], [50]. PM TFM is also a kind of PMSM, so its control equations can be expressed as follows within the control framework of PMSM.

 (18)

 (19)

 (20)

where *ω* is the angular frequency in electrical, is stator voltage vector, is stator resistance, , and  are stator current, *d*-axis and *q*-axis component; is stator flux vector,  and  are *d*-axis and *q*-axis inductance,  is PM flux, *p* is the number of pole pairs. Meanwhile, the voltage equations in *d-q* reference frame are as follows.

 (21)

 (22)

Given the voltage and current values at sampling instant *k*, the predicate current, torque and flux at instant *k*+1 can be expressed as follows.

 (23)

 (24)

 (25)

 (26)

where  and  are the predicted values of stator current for the sampling instant *k*+1 respectively;  is the sampling period; and  are the predicted values of torque and flux respectively, which are also the main concerns for the cost function in the following MPC control scheme.

The basic idea of MPC is to predict the future behavior of the variables over a time frame based on the model of the system. All predictions are evaluated based on a cost function and the prediction with minimized cost function is selected for future control actions. MPC has several merits, *e.g.*, the cost function is easy to incorporate nonlinear constraints and can include many control variables such as torque and flux. In order to take full use of the merits of MPC and overcome the demerits of DTC of high torque and flux ripples, several improvements for DTC and MPC were presented in our previous study [51], [52]. And an improved MPC scheme incorporating with a duty ratio optimization module was presented and discussed in [53]. It will be used in this work as the control method for the studied PM TFM. Fig. 8 shows a diagram of this control scheme.



Fig. 8. Diagram of the improved MPC scheme

The key issue of MPC is the definition of the cost function, which is related to the control objectives. The greatest concerns of PMSM drive applications are torque and stator flux. Therefore, the cost function is defined in such a way that both torque and stator flux at the end of control period are as close as possible to the reference values. In this paper, the cost function is defined as

 (27)

where , , and  are the reference torque and flux, predicted torque and flux respectively;  and  are linear predictions of torque and flux at the (*k*+*N*)–th instant, respectively; *k*1 and A are weighting factors. To obtain the same weight to torque and flux, *k*1 is defined as the ratio of rated torque over rated stator flux. The expression of duty ratio optimization module has the form as

, (28)

where *CT* and *Cψ* are two positive parameters. The idea of this method is that the larger difference between the reference and predicted torque values leads to larger duty ratio value [53].

Therefore, six parameters should be optimized in the control level. They are *A*, *N*, *CT*, *Cψ*, *Kp* and *Ki*, where *Kp* and *Ki* are the PI controller parameters. One objective and four constraints are considered for this level. The objective is to minimize the sum of root mean square errors (RMSE) of torque (*T*) and speed (*n*) in the steady operation period. At the same time, speed overshoot is needed to be minimized for this control system. The optimization model of the control system has the form as

 (29)

where *w*3 to *w*5 are weight factors; subscript *rated* means the values obtained from motor’s optimization model (17); *nos* is speed overshoot, which should be no larger than 2% compared with the rated speed 1800 r/min; *ts* is settling time, which should be no larger than 0.02 s after the load is applied to the control system. Therefore, two dynamic characteristic parameters of the control, namely speed overshoot and settling time are considered for the optimization (one is considered in objective and both are considered in constraints).

# Discussion and Results

For the optimization of this drive system, the first step is to verify the reliability of FEM-based analysis method for the performance evaluation of motor. Then the second step is to determine the multilevel optimization framework. Thirdly, approximate models will be constructed and their accuracy will be investigated. Finally, optimization results will be presented and discussed.

## Reliability of motor’s FEM-based analysis method

Fig. 9 illustrates the prototype of a PM TFM with SMC stator fabricated with the initial design scheme as shown in Table I. Table II lists the calculated and measured key motor parameters for this machine. It is found that the estimated performance parameters calculated from FEM-based method are well aligned with the experimental results, such as the inductance and cogging torque. Fig. 10 shows the measured motor speed against output torque by applying different DC link voltages. More details can be found in [48]. All the experimental results have verified the effectiveness of this FEM-based analysis method. Therefore, it is reliable to use it to optimize the investigated drive system.



(a) (b)

Fig. 9. Prototype of TFM with initial design scheme, (a) PM rotor, (b) 3 stack SMC stator

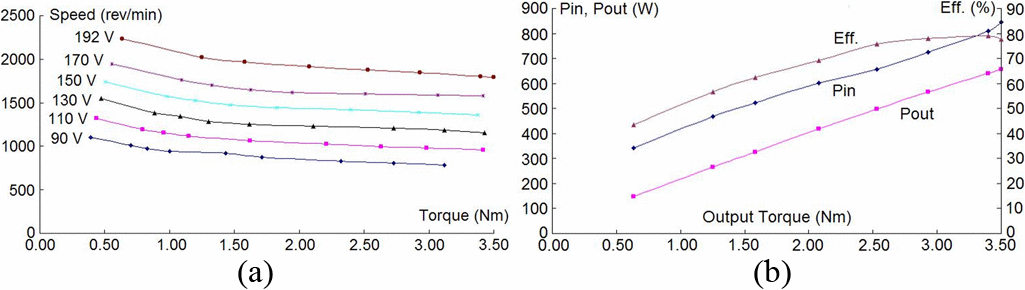


Fig. 10. Speed against output torque with different DC link voltages

TABLE II

Key Motor Parameters

|  |  |  |  |
| --- | --- | --- | --- |
| Parameter | unit | Calculated | Measured |
| Motor back *emf* constant | Vs | 0.247 | 0.244 |
| Phase resistance | Ω | 0.310 | 0.305 |
| Phase inductance | mH | 6.68 | 6.53 |
| Maximal cogging torque | Nm | 0.339 | 0.320 |

## DOE analysis and optimization framework determination

Firstly, for the 8 parameters at motor level, it was found that they can be divided into two subspaces by our design experience. The first subspace X1 includes *xm*1, *xm*2, *xm*6 and *xm*7, which are significant to the cost and output power of the motor. The second subspace X2 includes *xm*3, *xm*4, *xm*5 and *xm*8. Therefore, the optimization flowchart of the motor level has two sublevels.

Secondly, for the 6 parameters in the control level, after DOE analysis, it is found that except the third control parameter *CT*, other parameters have the same significant level. Table III shows the analysis of variance (ANOVA) results for the control level. In the table, the second column means the sum of square of deviations, the third column DF means degree of freedom, the fourth column Var. means variance, *F* column means the value of hypothesis testing with F distribution. *Fα* is a reference value for *F* distribution, *α* is significant level for hypothesis test. 0.01 is a generally used value for *α*, and *F*0.01 is 2.87. If the value of *F* is larger than *Fα*, the corresponding factor is a significant factor. Therefore, only the third parameter is a significant factor for objective of control level. Theoretically we can use SSOM with two subspaces for the control level. However, the significant space only has 1 factor, so we just select all six parameters as the same level.

In summary, the total optimization framework of this drive system has three levels as shown in Fig. 11. The first level is the subspace X1, which should be optimized to minimize the cost of motor material with respect to model (17). At this level, the parameters in the second subspace X2 are fixed. The second level is the X2 of motor parameters, which are optimized in terms of model (17) too. After the optimization of motor level, motor’s characteristic parameters, such as *R*, *L* and flux can be obtained as well, which will be used as the input parameters of MPC control system in the next level. The third level is the subspace of all the control parameters in model (29).



Fig. 11. Multilevel optimization flowchart for PM TFM drive system

TABLE III

DOE and ANOVA Data for Control Level

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Source | Sum. | DF | Var. | *F* | *F*α | Sig. |
| *x*c1 | 0.013 | 4 | 0.003 | 0.80 | 2.87 |  |
| *x*c2 | 0.015 | 4 | 0.004 | 0.88 | 2.87 |  |
| *x*c3 | 0.057 | 4 | 0.014 | 3.44 | 2.87 | \* |
| *x*c4 | 0.020 | 4 | 0.005 | 1.24 | 2.87 |  |
| *x*c5 | 0.013 | 4 | 0.003 | 0.76 | 2.87 |  |
| *x*c6 | 0.022 | 4 | 0.006 | 1.33 | 2.87 |  |
| Error | 0.083 | 20 | 0.004 | --- | --- | --- |
| Total | 0.139 | 24 | --- | --- | --- | --- |



Fig. 12. Kriging model for PM-flux at no-load situation

## Kriging model for motor analysis

To reduce the computational cost, Kriging model is used to approximate the 3D FEM in the optimization process. For this machine, FEM is employed to calculate three motor parameters, namely PM flux and core loss under no-load situation, and winding flux. To ensure the optimization efficiency, the accuracy analysis of Kriging model is needed. As the design parameters in X1 are significant to the motor performance, we only present the results of model error analysis for this level. At this level, though it includes four optimization parameters, two PM parameters (*xm*1 and *xm*2) are used for the field analysis under no-load situation and the other two winding parameters (*xm*6 and *xm*7) are only used for the field analysis under load situation.

For the no-load situation, 441 points are sampled to construct the Kriging model with quadratic polynomial as the deterministic term. Then, 6561 points are sampled for the model error analysis. After the analysis, it is found that RMSE of PM-flux is 0.01%; RMSE of core loss is 0.98%. Fig. 12 shows the constructed Kriging model of PM-flux. From this figure, it can be seen that the response surface is mostly flat; and Kriging model is very good for the FEM approximation.

For the calculation of winding flux under load situation, 661 points are sampled to construct the Kriging model with liner polynomial as the deterministic term. Then from the model error analysis with 3186 points, RMSE of winding-flux is 0.12%. Therefore, Kriging model is accurate to approximate motor’s electromagnetic characteristic parameters given by FEM.

TABLE IV

Optimization Results of PM TFM (Motor Level)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Par. | unit | Initial | Single Level | Multilevel |
| *xm*1 | deg | 12 | 10.65 | 10.0 |
| *xm*2 | mm | 9 | 8.0 | 7.6 |
| *xm*3 | mm | 9 | 8.45 | 8.0 |
| *xm*4 | mm | 8 | 7.65 | 7.85 |
| *xm*5 | mm | 10.5 | 9.15 | 10.8 |
| *xm*6 | turn | 125 | 117 | 110 |
| *xm*7 | mm | 1.25 | 1.23 | 1.27 |
| *xm*8 | mm | 1.0 | 1.0 | 0.90 |
| *η* | --- | 79.5% | 81.5% | 81.2% |
| *Pout* | W | 640 | 658 | 678 |
| *sf* | --- | 0.56 | 0.55 | 0.50 |
| *Jc* | A/mm2 | 4.72 | 5.88 | 5.97 |
| *T* | Nm | 3.40 | 3.49 | 3.60 |
| *Cost* | $ | 35.8 | 28.3 | 26.6 |
| *fm* | --- | 1.88 | 1.70 | 1.63 |
| FEM samples | --- | --- | 14000 | 2500 |

TABLE V

Optimization Results of MPC (Control Level)

|  |  |  |
| --- | --- | --- |
| Par. | Single Level | Multilevel |
| *xc*1 | 0.320 | 0.464 |
| *xc*2 | 6 | 6 |
| *xc*3 | 0.959 | 1.142 |
| *xc*4 | 0.03427 | 0.03471 |
| *xc*5 | 0.199 | 0.218 |
| *xc*6 | 2.698 | 2.904 |
| RMSE(*T*)/*Trated* | 4.17% | 4.24% |
| RMSE(*n*)/*nrated* | 0.10% | 0.07% |
| *nos* | 1.03% | 0.95% |
| *ts* | 0.01 | 0.01 |
| *fc* | 5.30% | 5.27% |
| Simulation calls | 14000 | 6000 |



Fig. 13. Dynamic performance of TFM with optimized MPC

## Optimization results of drive system

First of all, DEA is selected as the optimization algorithm in the multilevel optimization of this drive system. The algorithm parameters are: mutation scaling factor is 0.8, crossover factor is 0.8, and the maximum number of iteration is 1000 [21], [54]. Then *ε* in SSOM is defined as 1%. All weight factors are assumed to be 1 in this work. Tables IV and V show the optimization results obtained from the two methods, namely single level method and multilevel method proposed in this work. From these tables, we can draw the following conclusions.

1) Motor level. For the initial design scheme, motor efficiency is 79.5%, output power is 640 W, average torque is 3.40 Nm, material cost is $35.8 and the objective is 1.88.

For the single level optimization method with DEA and FEM, all the 14 parameters (8 motor parameters and 6 control parameters) are optimized at a single level strategy as shown in Fig. 3. The obtained motor efficiency is 81.5%, output power is 658 W, average torque is 3.49 Nm, material cost is $28.3 and the objective is 1.70. They are better than those of the initial design.

For the multilevel optimization method, after the optimization of motor level, the gained output power reaches 678 W and average torque reaches 3.60 Nm while the motor efficiency decreases to 81.2%. The cost is only $ 26.6, which is smaller than those from initial design and single level design schemes. And the objective of motor is 1.63. It can be seen that the motor objective is reduced by about 13.3% (0.25/1.88) and output power is increased by about 5.9% (38/640) by the proposed multilevel optimization method compared with initial design scheme. And these are also better than those from single level optimization with DEA. All the optimal design and the corresponding performance parameters of motor level can be seen in Table IV.

2) Control level. For the single level optimization, the objective is 5.30% and speed overshoot is 1.03%. After the multilevel optimization, the objective of control level is 5.27% and speed overshoot is 0.95%. Therefore, the dynamic performances with these two methods do not have significant differences. Fig. 13 illustrates the dynamic performance of the drive system provided by multilevel method. From this figure, it can be seen that the dynamic performances of speed and torque are very good.

3) For the computation cost, the cost of FEM analysis at motor level and the cost of Simulink simulation calls at control level are the largest computation burden for the whole optimization process. For the single level optimization method with DEA, about 14000 FEM samples and 14000 Simulink simulation calls are needed to achieve the optimal results. Actually, it is hard for an intelligent algorithm to deal with this kind of high-dimensional and highly nonlinear optimization problem of drive systems. It is time consuming and tends to find a local optimal point.

On the other hand, only 2500 (see Table IV) FEM samples are needed for motor level’s optimization by using the proposed multilevel optimization method, which is about 17.9% of the direct single optimization method. Moreover, about 6000 Simulink simulation calls are needed for the control level by using multilevel optimization method. This is less than half of the simulation cost of single level optimization method. Therefore, the proposed multilevel design optimization method can produce better solutions than single optimization method and can significantly reduce the computation cost as well.

# Conclusion

In this work, two system level design optimization methods are presented for electrical drive systems, namely single level design optimization method framework and multilevel design optimization method. Meanwhile, three techniques for improving the optimization efficiency are also presented, which are approximate models, DOE technique, and SSOM. A drive system with a PM TFM and an improved MPC controller is investigated to verify the effectiveness of the proposed methods. Compared with the schemes gained from initial design and single level method, it can be seen that the solutions obtained from multilevel method have many improvements, such as larger output power, larger torque and less material cost. Actually, both the objectives for motor level and control level have been improved for this drive system by using the multilevel method.

From the above discussions, it can be seen that system level design optimization method is necessary for electrical drive systems to achieve high steady and dynamic performance at the system level. Furthermore, the proposed multilevel method is efficient for the design optimization of high dimensional drive systems. It presents a practical effective approach to enable the efficient development of novel high performance drive systems with new materials, low cost and high performance for industrial applications, e.g., hybrid electric vehicles. This method can be also applied to other high dimensional design optimization problems in industrial applications. It will shorten the design cycle, reduce the design cost and improve the design efficiency for the industrial products in the early stage of product development.

The next step which will be investigated is the robust approach and multiobjective approach for system level design optimization of drive systems. In the multiobjective approach work, Pareto fronts for both deterministic and six sigma robust optimization frameworks will be presented and discussed. Future work will cover the power electronics and mechanical transmission parts for the design optimization of drive systems, and practical applications will be investigated. Furthermore, new multilevel and multidisciplinary methods will be proposed and compared for different drive systems with more closely coupled parts.

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