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Tuning of Predictive Controllers for Five-Phase Drives

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Abstract*: *Model Predictive Control is gaining attention as a versatile tool for multi-phase drives. In the direct digital control configuration the predictive controller can use a finite number of control actions. This allows the use of exhaustive optimization to derive the control action. Using a cost function it is possible to consider several control objectives, such as current, torque or flux tracking. Also, different additional criteria such as switching frequency, harmonic distortion or torque ripple can be considered. Tuning of the controller involves assigning a value to weighting factors used by the cost function. This has been studied in detail for predictive torque controllers. In this paper three design strategies for designing predictive current controllers are compared. The first uses fixed weighting factors, the second eliminates weighting factors by using a ranking based selection and the last considers a local optimization of the weighting factors.

Index Terms*: *Multiphase Systems, Model Predictive Control, Cost Function, Weighting Factors.

I. INTRODUCTION

Control of AC drives can be performed directly setting the converter states [1], [2]. Finite State Model Predictive Control (FSMPC) [3] (also known as Finite Control Set MPC) follows this strategy. It has been used in various applications including multi-phase and multilevel electrical systems [4]. The reason for this success is the ability of MPC to include different control objectives [5]. This ability is derived from the use of a Cost Function (CF) that discrete time wise optimized with respect to the control action. The CF is used to penalize deviation of variables such as currents, flux and torque from their reference values. In order to place more or less importance to variables, the CF can use Weighting Factors (WF). The design of WF has been considered in the context of FSMPC in [3] for Predictive Current Control (PCC) of multi-phase drives. Later works have mostly considered the case of Predictive Torque Control (PTC) (a review can be found in [6]).

Cost function design has a large influence on performance, not only over control objectives (such as error in current, flux or torque tracking), but also over other quantities of interest such as harmonic distortion, flux and torque ripple, and average switching frequency to name a few. It must be emphasized that if these quantities are included in the CF their actual values are not generally controlled as the system has not so many degrees of freedom [7]. After all, when conflicting control objectives are found, the FSMPC strategy finds a compromise solution at each discrete time period. The wave-forms produced in this way may contain values for harmonic distortion, flux and torque ripple, and average switching frequency that are not quite desired.

Different strategies can be found to deal with CF design for FSMPC that fall in the following (overlapping) classes:

S1. Constant values for the WF. The WF values are found using off-line having as objective the finding of a compromise behaviour in the operation range.

S2. CF with weighting functions (that can be made dependent on the operating point or not). This group is found in the literature as a separate category but is very similar to the next group in this list. Ranking schemes are the most popular method of this class. They have been used for PTC and will be applied here to PCC. One of the reasons supporting the use of this class is that WF tuning is unnecessary.

S3. Operating-point defined WF. Instead of fixed values, the WF can change on-line. The functional dependence is, however, designed off-line. This category covers S2 as a special case. A method pertaining to this class is proposed and evaluated in this work.

S4. CF that are mono-objective. This group eliminates the need for WF at the cost of a reduced flexibility. Despite this, the CF still need some design and this is done off-line as in S1.

S5. Determination of WF using optimization methods. This group is also a particular case of S1. The optimization method (genetic or other) provides additional support in the off-line phase of the designed WF values; hopefully reducing the number of required iterations.

S6. On-line determination of WF using fuzzy inference, alone or combined with ranking schemes. This group of methods is in fact included in S3. The fuzzy method may provide a better understanding of the role of the CF terms helping the design process.

In this paper, the determination of CF in 5-phase drives using PCC is tackled. Three CF design methods are compared, including a new method that belongs to S3 class and including the first reported application of S2 to PCC of multiphase drives.

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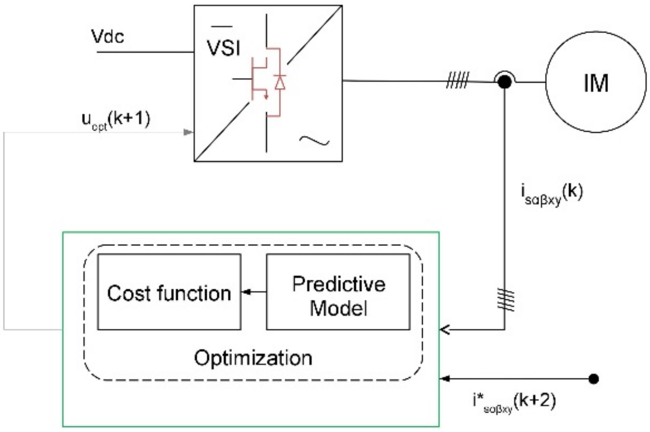

Fig. 1. Diagram of an AC drive using FSMPC.

In the next section the general scheme of PCC for 5-phase IM is briefly reviewed. The selected CF design methods are presented in more detail in section III. Simulation results using a 2-level voltage source inverter (VSI) driven 5-phase IM are presented in section IV, providing material for the conclusions shown at the end of the paper.

II. BACKGROUND ON PREDICTIVE CONTROL OF DRIVES

The study is conducted in the context of FSMPC of a 5-phase AC drive such as the one presented in Fig. 1. The scheme contains a computer providing the control action u each sampling period T_s. The actuation signal is denoted as the vector $u(k)$ indicating the state of the two-level VSI. The value for $u(k)$ should induce in the electrical system a certain behavior in terms of electrical variables such as currents, fluxes, etc. and, in the case of drives, mechanical variables. The reference signal r define the objective trajectories for the controlled electrical and/or mechanical variables.

A case of FSMPC is PCC, where the tracking of mechanical variables is done using an outer loop. This part provides reference values $r = i_s^*$ for stator currents i_s. The PCC must decide the state of the VSI so that appropriate voltages are produced. This is done at each sampling by means of

$$u^0(k) = \underset{u \in \mathbb{U}}{\operatorname{argmin}}\, J(k,u) \quad (1)$$

where, $\mathbb{U}$ is the set of all states of the VSI, and J is the cost function. As mentioned already, the CF must contain a term penalizing predicted tracking errors for stator currents

$$\hat{e}(k+2|k) = i_s^*(k+2) - \hat{i_s}(k+2|k) \quad (2)$$

where, $\hat{i_s}(k+2|k)$ is a prediction of stator currents and $i_s^*(k+2)$ is the reference value. The predictions depend on $u(k+1)$ and are obtained from a discrete-time model of the system (see [3] for details). In the case of multi-phase IM, the stator currents can be expressed in one $\alpha-\beta$ plane and several $x-y$ and z planes depending upon the IM windings and external connection. For a 5-phase IM with isolated neutral point, just $\alpha-\beta-x-y$ axes need to be considered [8]. Currents in $\alpha-\beta$ produce torque and currents in $x-y$ produce losses. For this reason, and in most cases, $i_{s\alpha,\beta} = (i_{s\alpha}, i_{s\beta})$ must follow a sinusoidal reference and $i_{sx,y} = (i_{sx}, i_{sy})$ a null reference.

$$J(k,u) = J_1(k,u) + \lambda_{xy} J_2(k,u) \quad (3)$$

$$J_1(k,u) = ||i^*_{s\alpha,\beta}(k+2) - \hat{i}_{s\alpha,\beta}(k+2|k,u)||^2 \quad (4)$$

$$J_2(k,u) = ||\hat{i}_{sx,y}(k+2|k,u)||^2) \quad (5)$$

where the weighting factors are used to place more importance on $\alpha-\beta$ or $x-y$ tracking. In most cases (strategies in S1), λ_{xy} is considered a parameter of the controller that is set off-line and kept constant. The choice of the WF will affect the balance of power conversion quality versus losses.

The PCC strategy uses (1) together with (3) to produce $u(k)$, which is sent to the VSI at each sampling period following the so called receding horizon strategy [5]. If a sufficiently accurate model is used ([9], [10]), the primary control objectives (current tracking in $\alpha-\beta$ and $x-y$ planes) are fulfilled. Other figures of merit such as THD, torque ripple and average switching frequency take values that are not directly controlled by the discrete-time optimization. This is due to the fact that a finite number of configurations of the VSI are available for the controller to deal with conflicting criteria. Then the actions taken can be optimal from the point of view of (3) but sub-optimal with respect to IM overall behavior. Thus, tuning of the cost function is a necessary step as will be shown in the next Section.

III. CF DESIGN METHODS

As stated in the introduction, there are in the literature several classes of methods for designing CF. In this work the focus is put on classes S1 (for being the most simple and used) and S2-S3 as they tackle a fundamental problem of class S1.

A. Class S1

CF design methods in this class treat the WF as parameters of the FSMPC. These parameters have an effect on different variables. As an example: a larger value for λ_{xy} in (3) will likely produce less THD [4]. Unfortunately the relationship between λ_{xy} and THD is not an easy one. The S1 design methodology consists on finding via extensive experimentation and simulation a compromise solution for the WF. A sub-optimal solution is given in many cases based on trial and error, rules of thumb and designers' insight.

In [11], the optimization of the WF is considered mathematically in full. Then, a meta cost function H arises in which the different figures of merit are combined. For the PCC case example such meta-CF takes the following form

$$H(\Lambda) = RMSCE(\Lambda) + \gamma_1 ASF(\Lambda) + \gamma_2 THD(\Lambda) \quad (6)$$

where RMSCE stands for Root Mean Squared Control Error (i.e. RMS stator current tracking error), THD is the stator current Total Harmonic Distortion, ASF is the Average Switching Frequency of the VSI, and Λ is a vector containing all WF considered by the cost function.

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Factors γ_i are weighting coefficients for this meta-CF. The WF design problem can now be stated as

$$\Lambda^0 = \underset{\Lambda}{\operatorname{argmin}}\, H(\Lambda) \quad (7)$$

Any general optimization method (such as genetic algorithms) can be used to provide a solution of 7. The computing requirements are not excessive as long as the dimension of Λ is not too large. Recall that, in most cases, just one or two WF are used. What is really important is to show to what extent the WF choice affects the considered figures of merit over the entire range of operation of the drive.

The (γ_i) must be set to concrete values before solving (7). This amounts to deciding how much of a figure of merit can be traded to improve another. This problem is application-specific and required expert knowledge. It can be argued that incorporating such knowledge in the mathematical form of (6) is difficult. Fuzzy representations might be of help for this task. Whatever the case, this difficulty is what hinders the application of the S1 method using a meta-cost function.

B. Class S2

Ranking-based methods allow to include different criteria in the CF without explicitly using WF. These methods belong to a class of mathematical problems known as Ranking and Selection Procedures (RSP). These are a sub-class of general simulation optimization algorithms in which the solutions are sought over a limited set of candidates. The seminal work for ranking means of normal distributions with known variances was introduced in [12]. Non-dominated sorting algorithms appeared later to sort a population into a hierarchy of non-dominated Pareto fronts from which solutions are drawn [13]. For CF design this can be applied by replacing the fixed WF (case S1) with a multi-objective optimization scheme. As a result there are no explicit WF rendering the tuning of WF unnecessary. For more details the reader is addressed to [6] and the numerous references that it contains.

The S2 scheme used here considers the J_1 and J_2 terms defined in (4) and (5) that should be minimized with respect to $u(k+1)$. To do so, the terms are evaluated for each possible state of the VSI u_i. An ascending sorting according to J_1 is produced by assigning a ranking value to each u_i depending on the position it occupies in the sorted list. The ranking value is denoted $r_1(u_i)$. It can be computed as the index in the list or any monotonous function of it. Similarly, a raking value $r_2(u_i)$ is obtained using J_2 as sorting criterion.

The r_i measure the relative qualities of each possible u_i. They are dimensionless variables related to values of the CF. The selection of the control action is then based on the minimum average value of its rankings. In mathematical form:

$$\mathrm{u}^0(k) = \underset{u \in \mathbb{U}}{\operatorname{argmin}}\big(\mathrm{r}_1(u) + \mathrm{r}_2(u)\big) \quad (8)$$

This amounts to converting the problem of optimizing from numerical into an ordinal problem (produced by the sorting). The WF are no longer tunable parameters as they are somehow subsumed in r_1 and r_2 due to the sorting and ranking operations.

The CF design methods in this class avoid the necessity of selecting the WF. Also, in a general case, they provide a balance of the conflicting terms in the CF that cannot be achieved by fixed values of the WF. This is so because the ranking procedure cannot be reduced to a linear expression such as (3) due to the sorting phase it relies on.

C. Class S3

This class is very broad making it difficult to explicit it completely. The following exposition is thus focused on a novel scheme for CF design.

It has been hinted before, and simulations later will show, that fixed values for the WF offer a compromise solution. One possible improvement is the use of values for the WF that are the most adequate for each operating point. In this case, instead of fixed parameters the WF are functions. The design of the functions are made off-line, for instance in the form of tables. The use of these functions on-line provide WF values according to some variables that represent the operating point as

$$\lambda_{xy}(k) = W(x(k)) \quad (9)$$

where $x(k)$ is the system state at discrete-time k, and W is a function that provides a value for λ_{xy} according to x.

In PCC of drives the operating point is mainly defined by the amplitude of stator currents in $\alpha - \beta$ (I_s) and the electrical frequency f_e. Other variables are connected to these two by the system dynamics and the control loops. Consequently, it is a good starting point to consider that $W(x(k)) = W(I_s(k), f_e(k))$.

The actual values for $W(x(k))$ can be obtained on-line from a table constructed from experiments in which I_s and f_e produce a grid that cover the entire range of operation. This can be denoted as $\mathbb{O} = \{I_{s,1}, I_{s,2}, \dots\} \times \{f_{e,1}, f_{e,2}, \dots\}$. For each pair in $\mathbb{O}$, an optimal value of the WF can be found as

$$\lambda^0_{xy,i}(k) = \underset{\lambda_{xy}}{\operatorname{argmin}}\, H(\lambda_{xy}, I_{s,i}, f_{e,i}) \quad (10)$$

where H is defined in the same way as in (6). Performing the adequate simulations for each point in $\mathbb{O}$, a table containing triples $(I_{s,i}, f_{e,i}, \lambda^0_{xy,i})$ is obtained. Function W can then be derived using a interpolation scheme or by curve fitting.

IV. SIMULATION RESULTS

As a case example, stator current control of a VSI driven 5-phase IM is considered. The controller is a FSMPC with a simple Euler-type prediction scheme. At each sampling period it explores the 31 possible voltage vectors that the VSI can produce and selects the one that minimizes the CF of (3), where the only weighting factor is λ_{xy} that takes into account the importance of deviations in $x - y$ plane over those of $\alpha - \beta$ plane.

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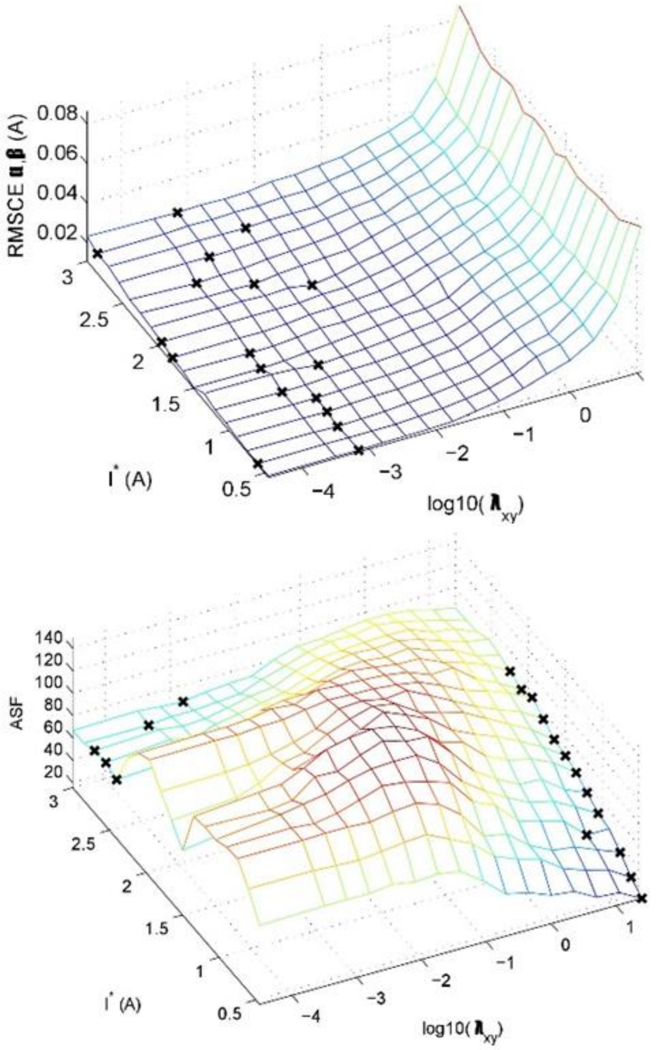

Fig. 2. RMS control error (top) and ASF (bottom) as a function of I^* and λ_{xy} (shown in log scale).

The control system is simulated in the Matlab environment using a continuous-time space-state representation of the system and a discrete-time subsystem for the control program. The computation time needed is carefully considered to produce realistic results. The IM electrical parameters are: $R_s = 19.45\ (\Omega)$, $R_r = 6.77\ (\Omega)$, $L_{ls} = 0.1007\ (\mathrm{H})$, $L_{lr} = 0.0386\ (\mathrm{H})$, $L_{1n} = 0.6565\ (\mathrm{H})$ and $P = 3$ pole-pairs. A value of 80 μs is used as sampling time. This value is within reach of modern DSP and has been reported in the [14]. The reference value (in the $\alpha - \beta$ plane) are sinusoidal values of frequency $f_e(Hz)$ and amplitude $I^*(A)$. For the $x - y$ plane the references are null as usual. The operating point is characterized by the reference provided by the outer control loop to the PCC.

The first example corresponds to S1 class and shows how different behaviors are obtained depending on the value of λ_{xy} [15]. To illustrate this, Fig. 2 (top) presents the RMS control error in $\alpha - \beta$ plane as a function of the IM load (I^*) and λ_{xy} for f_e= 50 (Hz). The times $(\times)$ marks on the surface are placed at the values of λ_{xy} that produce the least error for each value of I^*. It can be seen that, to provide the least error for different I^* different values of λ_{xy} are needed. Also, comparing with the results of Fig. 2 (bottom) it is apparent that the optimal value of λ_{xy} depends on the criterion used, for instance, optimizing for RMSCE might lead to a higher value of ASF and vice versa.

To further illustrate the case, results from a particular operating point are shown in Fig. 3, where two hodograms of i_s in $\alpha - \beta$ plane are shown for $I^* = 2.55\ (A)$ and $f_e = 50\ (Hz)$. The top one uses a WF set to the optimum value with respect to RMSCE for this operating point ($\lambda_{xy} = 7.1 \cdot 10^{-4}$). The bottom one uses $\lambda_{xy} = 0.5$ which is optimal for other operating points. It is clear that a fixed value of λ_{xy} is not optimal for operating points.

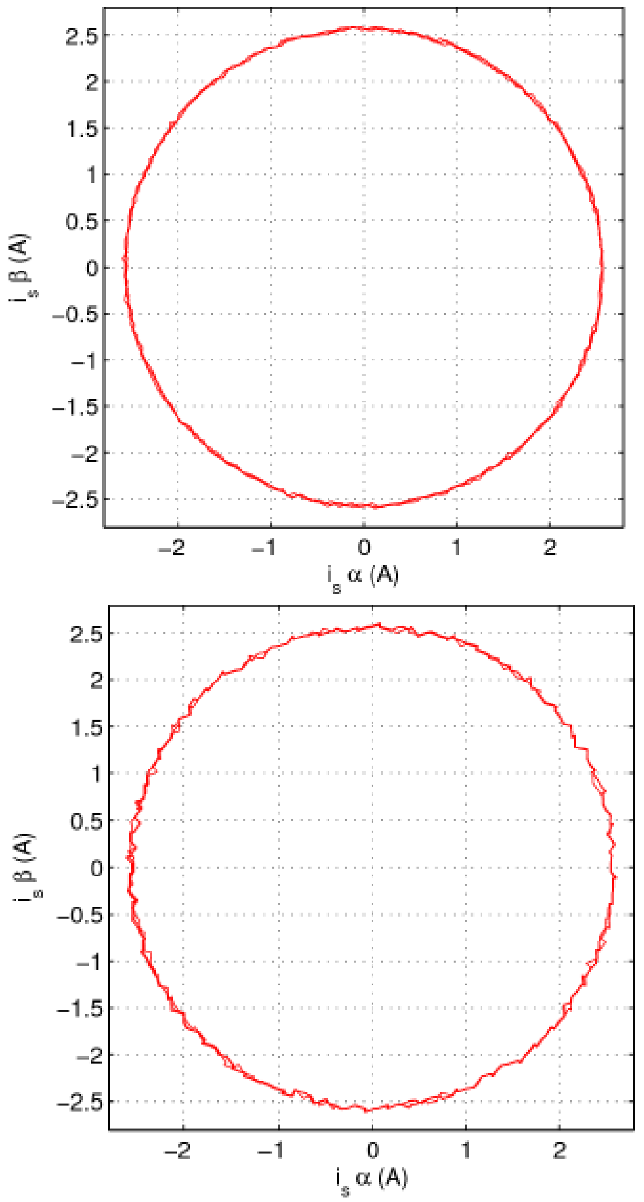

Fig. 3. Hodograms for i_s in $\alpha - \beta$ plane for two different values of λ_{xy}.

It is now the turn to simulate the design method from class S2 where no tuning of WF required. Using $f_e = 50\ (Hz)$, as in the previous cases, the results of Fig. 4 are obtained. Comparing with Fig. 2 it can be concluded that the S2 ranking strategy gives better results in terms of RMSCE than S1 with $\lambda_{xy} = 2.2$ (dash-dotted lines) but worse than S1 with $\lambda_{xy} = 0.2$ (dotted lines).

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As for ASF, the S2 strategy performs better than S1 with $\lambda_{xy} = 0.2$ but worse than S1 with $\lambda_{xy} = 2.2$. Thus, the S2 results can be seen as an intermediate solution between two cases of S1: with $\lambda_{xy} = 0.2$ and S1 with $\lambda_{xy} = 2.2$. From this it can be stated that the results offered by the S2 strategy are close to those of S1 and do not outperform them.

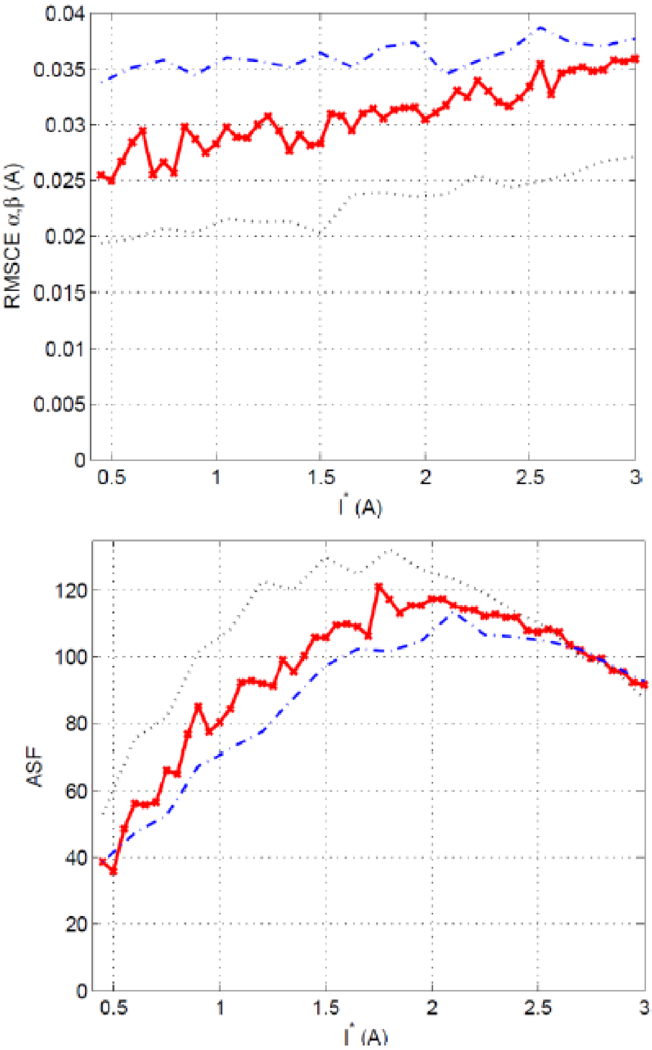

Fig. 4. RMS control error (top) and ASF (bottom) as a function of I^* for S2 (solid lines) and S1 with $\lambda_{xy} = 0.2$ (dotted lines) and $\lambda_{xy} = 2.2$ (dash-dotted lines).

In Fig. 5 instantaneous deviations of the stator currents values are presented for S1 and S2 strategies. It can be seen the relative amplitude of errors in $x - y$ (green) with respect to those of $\alpha - \beta$ plane (red). At each sampling time the errors for a pair of axes (i, j) are computed as

$$e_{ij} = (|i_{si}^* - \hat{i_{si}}| + |i_{sj}^* - \hat{i_{sj}}|)/2 \qquad (11)$$

For S1 and $\lambda_{xy} = 2.2$ the errors in $\alpha - \beta$ are lower than errors in $x - y$. However, for $\lambda_{xy} = 0.2$ the opposite is observed. In the case of S2 strategy, the results do not depend on λ. It is interesting to see that, for this method control errors are similar in both planes. This is a consequence of the ranking scheme used based on sorting.

In addition to the previous results, Table I presents some figures of merit. Again it can be seen that the S2 strategy produces a controller whose performance lies in between of two S1 cases. Thus, the main advantage of this method lies in the removal of WF tuning.

Table 1. Figures of Merit for Some CF

CF	RMSCE $\alpha - \beta$	RMSCE $x - y$	ASF
S1, $\lambda_{xy} = 0.2$	0.020	0.440	126
S1, $\lambda_{xy} = 2.2$	0.037	0.025	95
S2	0.030	0.029	109

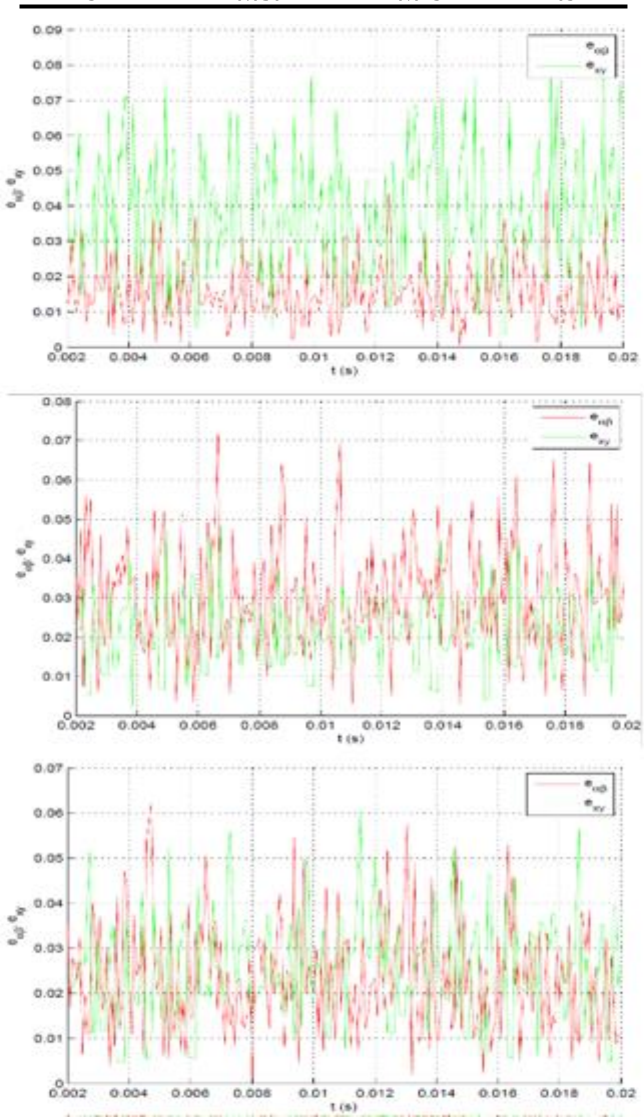

Fig. 5. Deviation of the stator currents in $\alpha - \beta$ and $x - y$ planes for S1 with $\lambda_{xy} = 0.2$ (top), for S1 with $\lambda_{xy} = 2.2$ (medium) and for S2 bottom).

Some results are now provided for the S3 strategy based on optimization of WF for each operating point. This require the definition of the γ_i. To make the comparison simpler $\gamma_2 = 0$ is selected, meaning that just RMSCE and ASF are considered as figures of merit. Also, as both quantities have different ranges they are normalized dividing by their maximum values. In this way the meta-CF considered for the simulations is

$$\lambda_{xy,i}^0 = \underset{\lambda_{xy}}{\operatorname{argmin}}\, RMSCE_n + \gamma_1 ASF_n \qquad (12)$$

where $RMSCE_n = RMSCE - (\max RMSCE)$ and $ASF_n = ASF - (\max ASF)$.

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Also for simplicity, just a single frequency will be explored $f_e = 50\ (Hz)$ (note that extending the analysis to other frequencies is straightforward). Fig. 6 shows the $\lambda^0_{xy,i}$ values vs. the I_i^* that will be used in the next test.

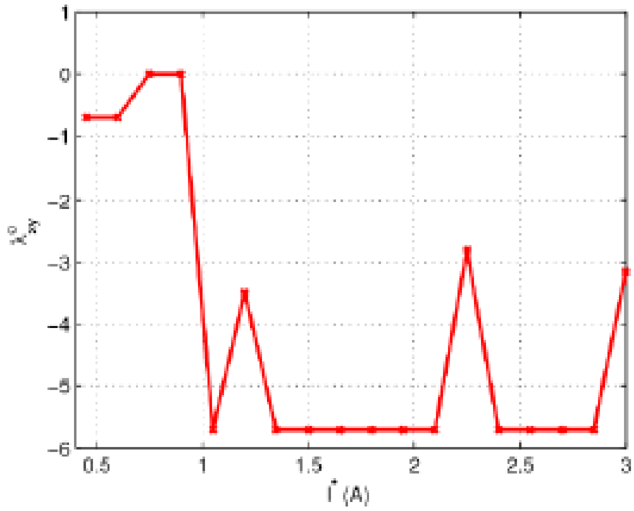

Fig. 6. Optimal values of λ_{xy} for each I^*.

In Fig. 7 the results for S3 with $\gamma = 0.4$ are shown. As in the previous case, two results from S1 strategy are added for ease of comparison. From Fig. 4 it can be concluded that for most of the operating range, S3 outperforms S1 and S2 as it produces less or nearly equal error with less or nearly equal switching frequency. Also it is clear that, by changing the γ_1 factor the designer can easily turn the design closer to fulfilling one objective (RMSCE) or the other (ASF).

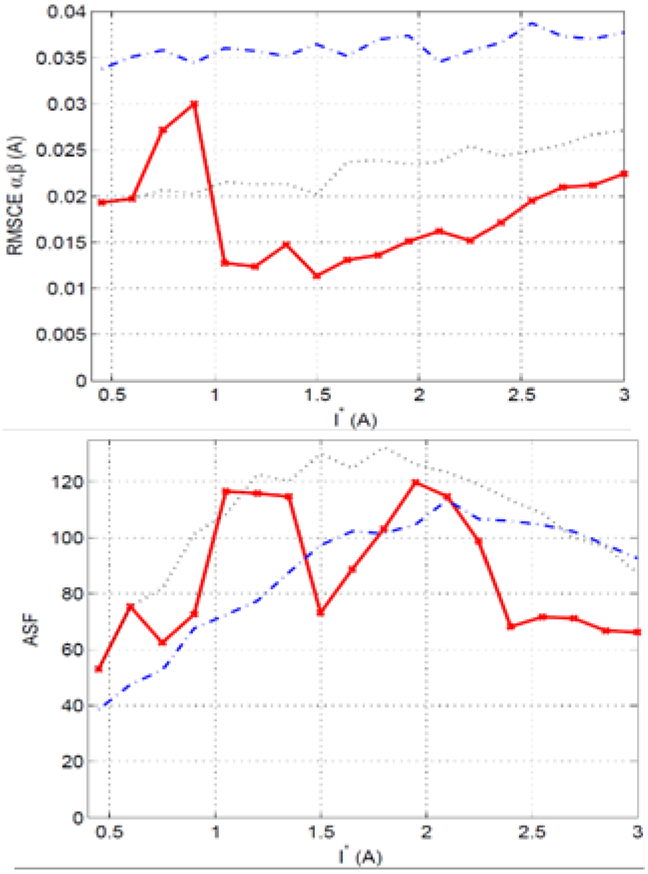

Fig. 7. RMS control error (top) and ASF (bottom) as a function of I^* for S3 (solid lines) and S1 with $\lambda_{xy} = 0.2$ (dotted lines) and $\lambda_{xy} = 2.2$ (dash-dotted lines).

V. CONCLUSIONS

The problem of cost function design has been considered in the context of multi-phase IM predictive control. A 5-phase IM with distributed windings has been used as a case example. The analysis performed using realistic simulations has considered three CF design strategies. Including ranking-based scheme with no weighting factors and a proposal by the authors that stems from local optimization of the WF. This novel strategy has been compared with the standard one and also with the popular ranking-based method. The obtained results indicate that the simple procedure of a fixed weighting factor is prone to poor results as the optimal weighting factor can depend on the operating point. The analysis shows that this dependence is not easy to deal with, as many figures of merit are involved.

To overcome these problems, the proposed CF design method uses a meta-cost function that is flexible enough to incorporate many figures of merit. These simulation-based conclusions must be corroborated with experimentation to finish the study and be able to make stronger assertions.

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