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Cooperative Decision-making Approach for Multi-objective Finite Control Set Model Predictive Control without Weighting Parameters

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***Abstract*—Finite control set model predictive control (FCS-MPC) has gained increasing popularity as an emerging control strategy for electrical drive systems. However, it is still a challenging task to optimize weighting parameters, as multiple objectives are involved in the customized cost function. A cooperative decision-making approach for FCS-MPC is proposed in this article, to solve the optimization problems with manifold control objectives. By splitting the cost function, the optimization problem underlying multi-objective FCS-MPC is separated into a series of decomposed optimization problems. By doing so, the dimension of the decomposed problem is reduced to one. To collect the information for decision-making, an efficient sorting algorithm is applied for each control objective. The theory behind the cooperative decision-making approach is comprehensively analyzed, to validate both the effectiveness and efficiency of the proposed scheme. More specifically, the highlight is the adaptive mechanism on the number of desired candidates, to obtain a decent performance for torque and flux. The candidate which minimizes the switching frequency is selected as the optimal. The proposed scheme is experimentally verified and compared with the existing FCS-MPC without weighting parameters.**

***Index Terms*—Model predictive control, multiple objectives, cooperative decision-making, weighting parameters optimization.**

I. Introduction

FINITE control set model predictive control (FCS-MPC) is enabled to online resolve the optimal solution for constrained quadratic programming (QP) problem, which highlights its increasing presence in the control of power converters and electrical drive systems [1], [2]. Thanks to the conceptual simplicity in the problem formulation, multiple conflicting disciplines and constraints are flexibly involved in the customized objective function [3], [4]. Regarding the discrete nature of power converters, the control inputs are directly enumerated for objective function minimization in a receding prediction horizon [5]. With the rapid development of digital controllers, FCS-MPC has spread from the process industry with a slow dynamic to a variety of power electronics applications, e.g., induction machine (IM) and permanent magnet synchronous machine (PMSM) drives, multi-level modular converters (MMCs) [6]–[8].

Predictive torque control (FCS-PTC) is one of the most popular schemes in the FCS-MPC family, as torque and stator flux are the optimized performance metrics in the electrical drive systems [9]. Despite that FCS-MPC achieves the attractive features of fast dynamic response, straightforward implementation and the ability to handle multi-objective nonlinear control systems, the balance between multiple control objectives is very difficult to be compromised [10], [11]. The technical challenges in the weighting factor optimization are the involvement of more conflicting objectives and increased computational burden. In [12], an empirical weighting value is assigned to each control variable, to indicate the importance of the corresponding tracking error term in the objective function. However, the trial-and-error method is a tedious and time-consuming task without theoretical analysis, which requires a large number of repetitive simulation implementations. To deal with this issue, several artificial intelligence (AI) methods have been studied in the literature. [13], [14] proposes an artificial neural network (ANN) method for the design of parameters in FCS-PTC. However, the combination of weighting parameters optimized by an offline ANN can be hardly adjusted as the step change occurs. In [15], the weighting parameters of FCS-MPC are fine-tuned in real-time on a low-cost hardware platform. However, the scale of ANN becomes larger when multiple criteria are involved in the formulated optimization problem. In [16], an ANN-based MPC with floating weighting factors for the active rectifier is proposed. Four control objectives and a decoupled stability objective are handled in the proposed ANN-based MPC. Although the contributions of multiple objectives are assigned by the aforementioned AI approaches, the effectiveness of ANN is significantly influenced by the training resources.

To avoid the usage of weighting parameters in the multi-objective FCS-MPC, previous references [17], [18] reformulate the objective function by a single-objective term (e.g., flux error term). In [18], a FCS-MPC scheme using flux vector is applied for PMSM drives. However, only the state variables can be unified according to the state-space

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model of the control plant. It is not practical to eliminate all the weighting parameters, when additional constraints (e.g., switching frequency) are evaluated in the customized objective function. As can be understood, the switching frequency term is very important to be included in the objective function. A lower switching frequency can improve both the efficiency and power rating of the converters.

Recently, several solutions have been proposed to address the adaptive tuning for weighting parameters. The main concept centers around the decomposition of a high-dimension optimization problem. As can be understood, the weighting parameters are directly eliminated when the FCS-MPC optimization problem is separated into a series of decomposed problems. By doing so, the dimension of the distributed problem is reduced to 1. Optimization effectiveness means the ability to optimize the weighting factors for more conflicting control targets, while efficiency is the cost of increased algorithm complexity for weighting factor optimization. However, how to obtain the optimal solution with improved optimization effectiveness and efficiency is still an open issue. In [19], a ranking approach for multi-objective optimization is proposed to investigate the potential optimal solution. Although the ranking approach is conceptually simple, an additional weighting coefficient for each criterion is required. A quick-sort algorithm is incorporated into the FCS-MPC scheme to tackle more conflicting control targets (e.g., switching frequency) in [20]. The sums of the assigned ranking values are subsequently compared for performance evaluation. However, it is hard to select the optimal for the circumstances that the sums of ranking values are equal for different control inputs. In [21], the torque and flux error terms in the multi-variable FCS-MPC scheme are investigated in a generalized sequential manner. The effectiveness of the proposed method is impaired by the inherent drawback of the hierarchical structure. It is noteworthy that the number of control inputs is significantly narrowed when a certain control objective is optimized. In [22], a fixed switching frequency MPC without weighting factor is presented. The optimal solution is generated by two desired vectors with duty cycles, which are obtained by optimizing the single-objective terms. In [23], an even-handed criterion that results in a lower cross-error is applied for the selection of optimal vector in FCS-MPC. Although the priorities of the control objectives have been carefully assigned, the before-mentioned limitation of the hierarchical optimization structure should be taken into consideration when multiple control targets are involved. In [24], the preselected switching sequences below the constraints are optimized in a concurrent manner. Despite that the proposed method is allowed to deal with multiple control objectives simultaneously, the design of the boundaries for all the criteria is still a cumbersome process. An effective FCS-MPC scheme for PMSM drive without the involvement of weighting parameters is presented in [25]. It should be mentioned that only the torque and flux tracking errors are optimized in the proposed scheme. The proposed scheme becomes more complicated when the switching frequency term is involved in the objective function. Authors in [26] propose a novel boundary-based method for FCS-MPC without weighting factor. The torque boundaries are optimized online to monitor the number of valid vectors. In [27], a multi-objective genetic algorithm is presented for weighting factor optimization of the FCS-MPC schemes. To find the Pareto optimal set, the genetic algorithm entails a high computational burden for online iteration. A high-dimension weighting parameter problem is optimized in [28]. The multiple cost functions whose hierarchy is determined by the error quantities, but the thresholds still require tuning. Although the abovementioned methods can resolve the optimal solution by collecting information from the decomposed problems, the improvement on both the optimization effectiveness and efficiency is still of great importance.

The motivation of this article is to obtain the optimal solution from the results of a series of decomposed problems, which adaptively modifies the relationship between multiple conflicting objectives for FCS-MPC schemes. By splitting of the objective function, the dimension of optimization problem underlying multi-objective FCS-MPC is reduced to 1. Thus, the issue of weighting parameters optimization is replaced by obtaining the optimal solution from the collected results of the decomposed problems, which are preselected by a fast-sorting algorithm. In the proposed cooperative decision-making approach, the optimization for torque and flux (performance metrics of the control plant) are regarded as the master problems, while minimizing the switching frequency is considered as the subproblem. The candidate vectors are initially generated by an adaptive mechanism between the master problems, which show a high similarity with the collected results. To reduce the algorithm complexity, fewer circumstances are categorized in the subproblem. A proper number of candidate vectors is determined by modifying the number of collected results for the master problems. The candidate vector which minimizes the switching frequency is selected as the optimal solution for the multi-objective FCS-MPC problem. Compared with the state-of-the-art FCS-MPC schemes without weighting parameters, the effectiveness and efficiency of the proposed cooperative decision-making approach are experimentally validated on a 2.2 kW IM testbench. The contributions of the article are summarized as follows.

1) The relationship between multiple objectives in the FCS-MPC schemes are fine-tuned by the proposed cooperative decision-making approach. The cumbersome process of weighting parameters design is eliminated by separating FCS-MPC into a series of decomposed problems. By doing so, the design and implementation of FCS-MPC is significantly improved without the need for tuning of weighting parameters.

2) The number of control inputs are sufficient for the master problems, which overcomes the drawback of the hierarchical structure. The proposed algorithm improves its effectiveness by resolving the global optimal for the master problems. Due to an avoidance of a worst case for both the master problems, a smaller ripples are obtained in the performance metrics.

3) The algorithm complexity is reduced by modifying the collected results in the master problems. Owing to a proper number of candidate vectors, fewer circumstances are considered in the subproblem. The number of comparisons is reduced by a fast-sorting algorithm. Based on the above, the proposed decision-making approach is computationally efficient.

The rest of the article is organized as follows. The problem formulation of multi-objective FCS-MPC scheme is described in Section II. The principle of cooperative decision-making approach is investigated in Section III. The proposed cooperative decision-making approach for multi-objective FCS-MPC is experimentally verified in Section IV. Finally, Section V concludes this article.

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II. Problem Formulation of Multi-objective FCS-MPC

A. Control Plant Description

The state-space model of IM is represented in the stationary reference frame,

$$\begin{bmatrix}\dfrac{d\hat{\boldsymbol{\psi}}_{\mathrm{s}}}{\mathrm{dt}}\\[2mm] \dfrac{d\hat{\boldsymbol{\psi}}_{\mathrm{r}}}{\mathrm{dt}}\end{bmatrix} = \left(\begin{bmatrix}-R_{\mathrm{s}} & 0\\ 0 & -R_{\mathrm{r}}\end{bmatrix}\begin{bmatrix}L_{\mathrm{s}} & L_{\mathrm{m}}\\ L_{\mathrm{m}} & L_{\mathrm{r}}\end{bmatrix}^{\mathrm{T}} + \begin{bmatrix}0 & 0\\ 0 & j\omega\end{bmatrix}\right)\begin{bmatrix}\hat{\boldsymbol{\psi}}_{\mathrm{s}}\\ \hat{\boldsymbol{\psi}}_{\mathrm{r}}\end{bmatrix} + \begin{bmatrix}1 & 0\\ 0 & 0\end{bmatrix}\begin{bmatrix}\boldsymbol{u}_{\mathrm{s}}\\ 0\end{bmatrix}, \tag{1}$$

$$\begin{bmatrix}\boldsymbol{i}_{\mathrm{s}}\\ \boldsymbol{i}_{\mathrm{r}}\end{bmatrix} = \begin{bmatrix}L_{\mathrm{s}} & L_{\mathrm{m}}\\ L_{\mathrm{m}} & L_{\mathrm{r}}\end{bmatrix}^{\mathrm{T}}\begin{bmatrix}\hat{\boldsymbol{\psi}}_{\mathrm{s}}\\ \hat{\boldsymbol{\psi}}_{\mathrm{r}}\end{bmatrix}, \tag{2}$$

where the stator and rotor resistances are represented by R_{s} and R_{r}, the stator, rotor and magnetizing inductances are denoted by L_{s}, L_{r} and L_{m}, respectively. The stator and rotor currents are $\boldsymbol{i}_{\mathrm{s}}$ and $\boldsymbol{i}_{\mathrm{r}}$, $\hat{\boldsymbol{\psi}}_{\mathrm{s}}$ and $\hat{\boldsymbol{\psi}}_{\mathrm{r}}$ are the estimated stator and rotor flux, ω denotes the rotor angular speed. The applied topology of the inverter is a 2-level voltage-source-inverter (VSI). The gate drive signal of the upper power device in the phase-leg configuration is denoted by S_a, S_b, S_c, respectively. As the upper power device turns on, the corresponding gate drive signal is 1. Otherwise, the gate drive signal is 0. The control input $\boldsymbol{u}_{\mathrm{s}}$ is the applied voltage vector, which is transformed into the stationary $\alpha\beta$ frame,

$$\boldsymbol{u}_{\mathrm{s}\alpha\beta} = \begin{bmatrix}\dfrac{2}{3} & -\dfrac{1}{3} & -\dfrac{1}{3}\\[2mm] 0 & \dfrac{1}{\sqrt{3}} & -\dfrac{1}{\sqrt{3}}\end{bmatrix}\boldsymbol{u}_{\mathrm{sabc}}. \tag{3}$$

B. Multi-objective FCS-MPC

The FCS-MPC schemes solve the multi-objective optimization problem by minimizing the tracking errors between the predicted and reference values. Multiple conflicting targets, e.g., torque, flux and switching frequency are evaluated in the formulated objective function. Regarding the time-delay compensation, the future behavior of stator current and flux $\hat{\boldsymbol{i}}_{\mathrm{s}}(k+2)$ and $\hat{\boldsymbol{\psi}}_{\mathrm{s}}(k+2)$ are calculated by forward Euler discretization,

$$\hat{\boldsymbol{\psi}}_{\mathrm{s}}(k+1) = \hat{\boldsymbol{\psi}}_{\mathrm{s}}(k) + T_{\mathrm{s}}\left(\boldsymbol{u}_{\mathrm{s}}(k) - \boldsymbol{i}_{\mathrm{s}}(k)\cdot R_{\mathrm{s}}\right), \tag{4}$$

$$\hat{\boldsymbol{i}}_{\mathrm{s}}(k+1) = (1 - \frac{T_{\mathrm{s}}}{\tau_\sigma})\cdot \boldsymbol{i}_{\mathrm{s}}(k) + \frac{T_{\mathrm{s}}}{\tau_\sigma R_\sigma}\cdot[k_r(\frac{1}{\tau_r} - j\omega(k))\hat{\psi}_{\mathrm{r}}(k) + \boldsymbol{u}_{\mathrm{s}}(k)], \tag{5}$$

$$\hat{\boldsymbol{\psi}}_{\mathrm{s}}(k+2) = \hat{\boldsymbol{\psi}}_{\mathrm{s}}(k+1) + T_{\mathrm{s}}\left(\boldsymbol{u}_{\mathrm{s}}(k+1) - \hat{\boldsymbol{i}}_{\mathrm{s}}(k+1)\cdot R_{\mathrm{s}}\right), \tag{6}$$

$$\hat{\boldsymbol{i}}_{\mathrm{s}}(k+2) = (1 - \frac{T_{\mathrm{s}}}{\tau_\sigma})\cdot \hat{\boldsymbol{i}}_{\mathrm{s}}(k+1) + \frac{T_{\mathrm{s}}}{\tau_\sigma R_\sigma}\cdot[k_r(\frac{1}{\tau_r} - j\omega(k))\hat{\boldsymbol{\psi}}_{\mathrm{r}}(k+1) + \boldsymbol{u}_{\mathrm{s}}(k+1)], \tag{7}$$

where T_{s} is the sampling period, $k_{\mathrm{r}} = L_{\mathrm{m}}/L_{\mathrm{r}}$, $R_\sigma = R_{\mathrm{s}} + k_{\mathrm{r}}^2\cdot R_{\mathrm{r}}$, $\sigma = 1 - (L_{\mathrm{m}}^2/L_{\mathrm{s}}L_{\mathrm{r}})$ and $L_\sigma = \sigma\cdot L_{\mathrm{s}}$ are the parameters of IM. The predicted torque $\hat{T}(k+2)$ is expressed as

$$\hat{T}(k+2) = \frac{3}{2}p\cdot Im\left\{\hat{\boldsymbol{\psi}}_{\mathrm{s}}(k+2)\cdot\hat{\boldsymbol{i}}_{\mathrm{s}}(k+2)\right\}. \tag{8}$$

The objective function J with the involvement of torque, flux and switching frequency terms is formulated as

$$J = \left[T^* - \hat{T}(k+2)\right]^2 + \lambda_\psi\left[\|\boldsymbol{\psi}_s^*\| - \left\|\hat{\boldsymbol{\psi}}_s(k+2)\right\|\right]^2 + \lambda_{\mathrm{sw}}\cdot n_{\mathrm{sw}}^2 + I_m(k+2), \tag{9}$$

where λ_ψ and λ_{sw} are the weighting parameters. n_{sw} is the number of switching changes in a sampling interval, $I_m(k+2)$ is the limitation term for stator current magnitude,

$$I_m(k+2) = \begin{cases} 0, & \mathit{if}\ |\boldsymbol{i}_{\mathrm{s}}(k+2)| \le |\boldsymbol{i}_{\mathrm{smax}}| \\ \gamma >> 0, & \mathit{if}\ |\boldsymbol{i}_{\mathrm{s}}(k+2)| > |\boldsymbol{i}_{\mathrm{smax}}| \end{cases} \tag{10}$$

As can be understood, multiple control objectives are simultaneously optimized in the objective function of FCS-MPC (see Fig. 1). Note that the weighting parameters, e.g., λ_ψ and λ_{sw} are applied to balance the importance of all the control objectives. Therefore, the selection of weighting parameters has a significant influence on the performance metrics of FCS-MPC schemes.

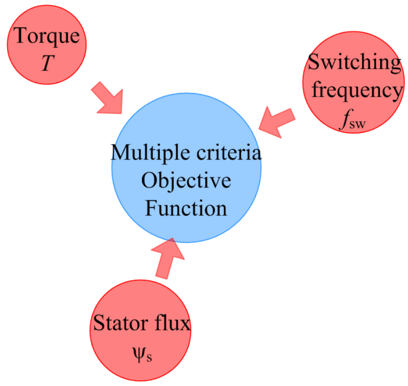

Fig. 1. Multiple control objectives in FCS-MPC.

III. Principle of Proposed Cooperative Decision-making Approach

A cooperative decision-making approach is proposed for the multi-objective FCS-MPC schemes, to avoid the time-consuming task of weighting parameters design. As shown in Fig. 2, the proposed approach consists decomposition of the FCS-MPC problem, results collection of the decomposed problems, adaptive mechanism for the master problem and the decision-making for the subproblem. Owing to that there is no weighting factor optimization for the current limitation term, the current limitation term is not reflected in Fig. 2.

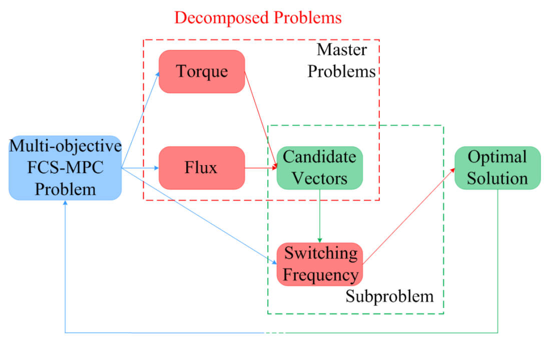

Fig. 2. Close-loop schematic of the proposed cooperative decision-making approach.

A. Decomposition of the FCS-MPC problem

The concept behind the proposed approach is to separate the multi-objective FCS-MPC (which is a high-dimension optimization problem) into a series of decomposed problems. As shown in Fig. 3, the decomposed problems are optimizing the torque, flux and switching frequency terms, respectively. The tracking error terms (11-13) are expressed as

$$J_1 = \left[T^* - \hat{T}(k+2)\right]^2 + I_m(k+2), \tag{11}$$

$$J_2 = \left[\|\psi_s^*\| - \left\|\hat{\psi}_s(k+2)\right\|\right]^2 + I_m(k+2), \tag{12}$$

$$J_3 = n_{\text{sw}}^2 + I_m(k+2). \tag{13}$$

It is noteworthy that the current limitation term is not a conflicting control objective in the weighting factor optimization of FCS-MPC schemes. There is no requirement to design or optimize a weighting factor for the current limitation term. The optimization of the parameter γ has no compromise on the performance of the other control objectives. Thus, the design of weighting parameters is not required, because the dimensions of the decomposed problems are 1. Based on the above, "how to deal with the results of the decomposed problems" has become an open issue.

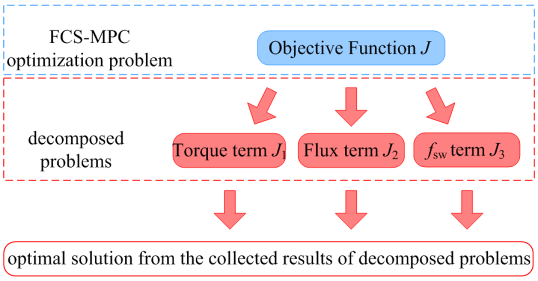

Fig. 3. Decomposition of the multi-objective FCS-MPC problem.

B. Results Collection of the Decomposed Problems

The design of weighting parameters is eliminated by the decomposition of multi-objective FCS-MPC problem. The results of the decomposed problems are subsequently collected by a fast-sorting algorithm. The fast-sorting algorithm for torque, flux and switching frequency terms are carried out in a concurrent manner. As shown in Fig. 4, the results collection for the torque term is illustrated as an example. Note that there are two arrays u_{T} and J_1 to collect the control inputs and the values of tracking error term, respectively. i denotes the index of the control input. u_0 and $J_1(u_0)$ are initially saved in the first element of the arrays. If the index i is an even value ($i = 2m$), e.g., i = 2, the value $J_1(u_2)$ is compared with $J_1[1]$. u_2 and $J_1(u_2)$ are saved in $u_{\text{T}}[2]$ and $J_1[2]$, when $J_1(u_2)$ $\geq$J$_1$[1]. Otherwise, a comparison between $J_1(u_2)$ and $J_1[0]$ is conducted. $u_{\text{T}}[0]$ is replaced by u_2 when $J_1(u_2) < J_1[1]$. Conversely, $u_{\text{T}}[1]$ is replaced by u_2. If the index i is an odd value ($i = 2m + 1$), the value $J_1(u_{\text{i}})$ is compared with $J_1[m]$. The aim of the fast-sorting algorithm is to obtain the rearranged control inputs, for which the value of tracking error term are monotonically increasing. The number of control inputs for each control objective is 7. As shown in Fig. 5, the vectors $u_T[0-6]$ are applied for torque optimization, and the vectors $u_F[0-6]$ are applied for flux optimization. If we optimize torque, flux and switching frequency in a concurrent manner, 7 more vectors $u_{sw}[0-6]$ are required also for the optimization of switching frequency. Therefore, the total number of vectors is reduced from 21 to 14 in the proposed method.

C. Adaptive Selection Mechanism for the Master Problems

The control inputs are rearranged for both the master problems that the values of tracking error terms are monotonically increasing. The description of the adaptive selection mechanism for the master problems is depicted in Fig. 5. The first three control inputs for the two master problems $u_{\text{T}}[0-2]$ and $u_{\text{F}}[0-2]$ are initially selected, to achieve an overall decent performance (because the corresponding tracking errors are smaller). As can be understood, a considerable good performance for torque and flux can be obtained by the vector which shows the similarity with one of the preselected control inputs (for the two master problems).

However, the drawback is that the number of the candidate vectors generated by $u_{\text{T}}[0-2]$ and $u_{\text{F}}[0-2]$ is uncertain, for which the number ranges from 0 to 3. Note that the subproblem optimization is categorized by the number of candidate vectors n. The optimal solution can not be resolved in the FCS-MPC optimization problem, if there is no candidate vectors for the two master problems. On the contrary, the torque and flux performance is not satisfactory, when the optimal solution is selected from the three candidate vectors in the suboptimal solution. Therefore, the desired number of candidate vectors is 1 or 2.

To obtain the desired number of candidate vectors, an adaptive mechanism on the number of preselected control inputs for flux optimization (Master problem 2). As shown in Fig. 5, one more control input in u_{F} is preselected as $n < 1$. Otherwise, the number of preselected control inputs in u_{F} is reduced as $n > 2$. The adaptive number of preselected control inputs is applied in the current sampling period, and defined as the initial value in the next interval.

The merits of the proposed adaptive selection mechanism is clarified as twofold. First, an overall decent performance is achieved by the candidate vector which shows the similarity with the preselected control inputs for both the master problems. Moreover, a worst case for torque and flux is avoided, which results in a smaller ripple. The latter advantage is a few number of circumstances are considered in the subproblem, which leads to a reduced algorithm complexity.

D. Subproblem Optimization

The subproblem optimization aims to select the optimal solution from the candidate vectors, by minimizing the number of switching changes. As $n = 1$, the only candidate vector is directly considered as the optimal solution, which achieves a considerably decent performance in terms of torque and flux. If there are two candidate vectors, the one minimizes J_3 (the number of switching changes) is selected as the optimal.

According to the collected results for torque and flux, the proposed algorithm obtains the common candidates which performs well in terms of torque and flux. Moreover, the worst case is always avoided for both torque and flux. As the common candidates are obtained, the switching frequency term is optimized on the basis of a good torque and flux performance. Therefore, the proposed algorithm can achieve satisfactory performance metrics for all the control objectives.

E. Performance Evaluation

Comparisons between a series of FCS-MPC schemes without weighting parameters (by the decomposition of multi-objective optimization problem) are summarized in TABLE. I.

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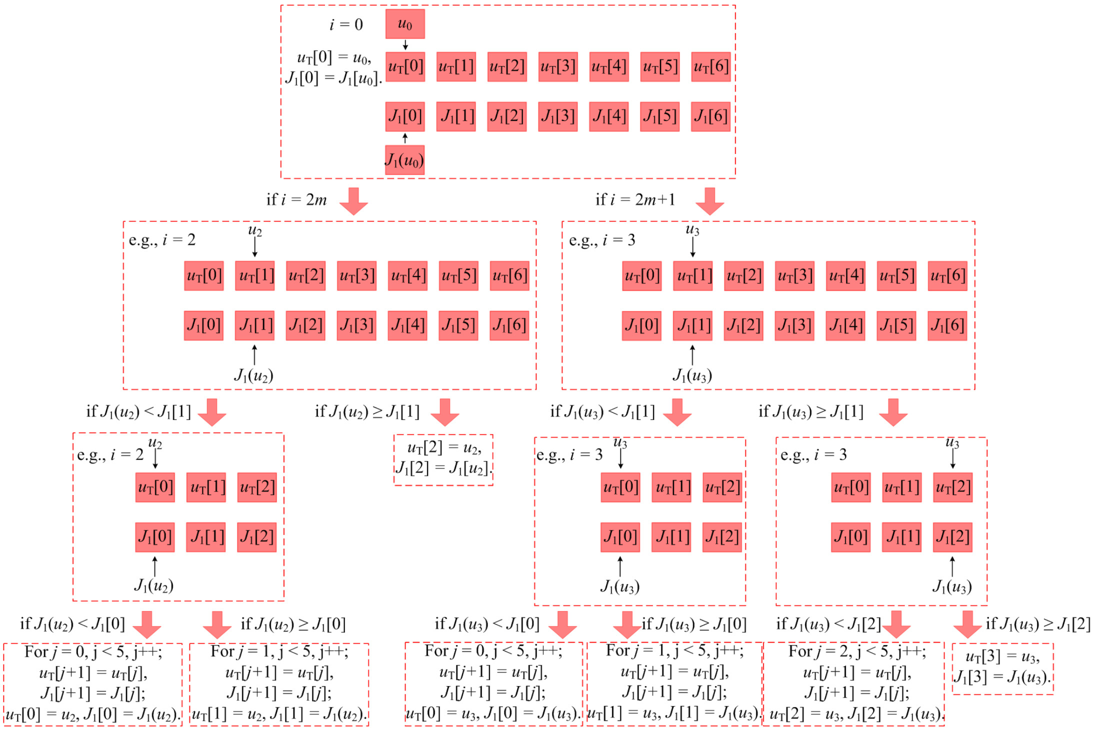

Fig. 4. Description of the fast-sorting algorithm.

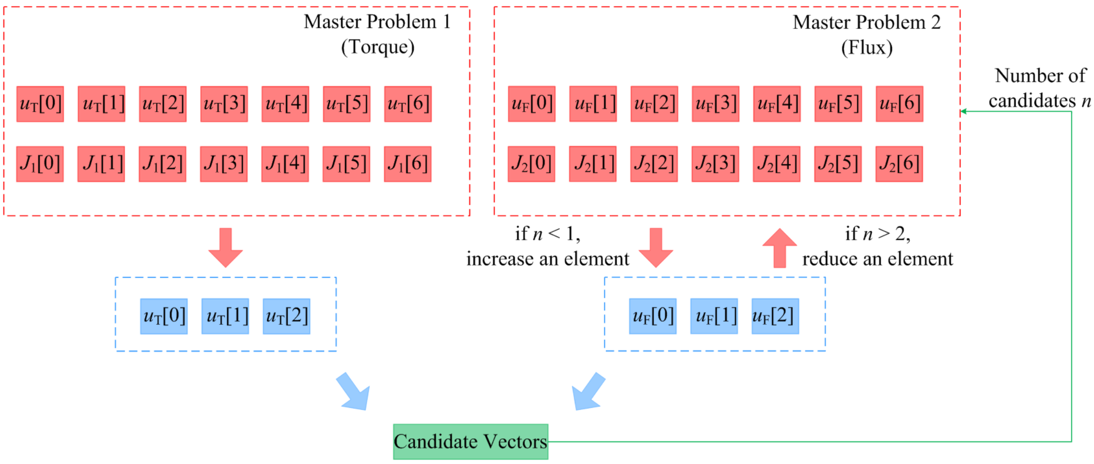

Fig. 5. Description of the Adaptive Mechanism for the Master Problems.

All the three methods has the merits of relationship optimization between multiple control objectives, adaptive tuning during the transient state and no requirement of extra parameters. Compared with the state-of-the-art methods [21, 25], both the effectiveness and efficiency of the proposed approach are improved. It is noteworthy that the proposed approach is not restricted by the number of control inputs and control targets. Both the worse cases for torque and flux are avoided. More specifically, the algorithm complexity is reduced due to a few number of circumstances.

An overall control diagram of the proposed method is shown in Fig. 6. The merits of the proposed control method are summarized as below.

1) The weighting factors of multiple conflicting objectives in the FCS-MPC schemes are fine-tuned by the proposed cooperative decision-making approach. Moreover, the importance for all the control objectives is adaptively optimized during the transient state.

2) The effectiveness of weighting factor optimization is improved. All the control inputs are fully optimized in the master problems. The number of control inputs are sufficient for the master problems, which overcomes the drawback of the hierarchical structure. A smaller ripples are obtained in the performance metrics due to an avoidance of the worst case.

3) The algorithm efficiency of weighting factor optimization is improved. The number of comparisons is reduced by a fast-sorting algorithm. Only two circumstances are considered in the subproblem. The proposed cooperative decision-making approach is computationally efficient.

IV. Experimental Verification

The proposed cooperative decision-making approach for multi-objective FCS-MPC is investigated on a 2.2 kW lab-built IM testbench (see Fig. 7). The applied structure of motor is a pair of 2.2 kW squirrel-cage induction machine. As shown in Fig. 7, the left IM (E) driven by the Servostar inverter (B) is used as the main machine, the right one (F) driven by the Danfoss FC-302 inverter (A) is used as the load

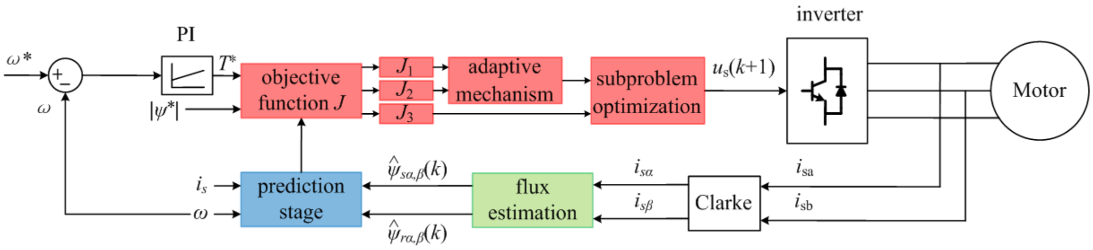

Fig. 6. Control diagram of the proposed method.

TABLE I
COMPARISONS BETWEEN A SERIES OF FCS-MPC SCHEMES WITHOUT WEIGHTING PARAMETERS

Methods	Generalized Sequential [21]	Effective Method [25]	Cooperative Decision-making
Optimization the importance between multiple objectives	✓	✓	✓
Adaptive tuning during the transient state	✓	✓	✓
No extra parameters	✓	✓	✓
No limitation on the number of control inputs and targets	×	✓	✓
Avoidance of a worse case for torque and flux	×	✓	✓
Reduced algorithm complexity	✓	×	✓

machine. The parameters of the IMs are listed in TABLE. II. A 1.4 GHz self-made real-time controller is applied for the implementation with a sampling period $T_s = 62.5\ \mu$s. The proposed algorithm is compared with the GS-MPC [21] and effective MPC [25]. The weighting parameters are eliminated in all the comparative schemes by the decomposition of the FCS-MPC problems.

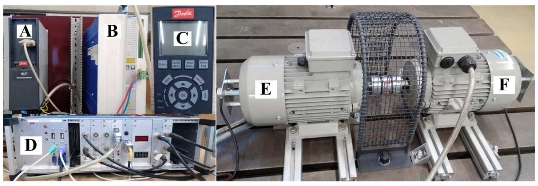

Fig. 7. Experimental Setup. (A) 3.0 kW Danfoss FC-302 inverter, (B) 14 kVA Servostar620 inverter, (C) Control panel (D) Self-made real-time controller (E) Main machine (F) Load machine.

TABLE II
PARAMETERS OF THE INDUCTION MACHINE.

Parameters	Values
DC link voltage $V_{\mathrm{dc}}[V]$	582
Stator resistance R_{s} [Ω]	2.68
Rotor resistance R_{r} [Ω]	2.13
Magnetizing inductance L_{m} [H]	0.275
Stator inductance L_{s} [H]	0.283
Rotor inductance L_{r} [H]	0.283
Speed PI controller gains k_{p}, k_{i} [/]	0.23, 5.38
Pole pairs $\mathrm{N_p}[/]$	1
Nominal rotor speed ω_{nom} [rpm]	2772
Nominal stator flux ψ_{snom} [Wb]	0.71
Nominal torque T_{nom} [Nm]	7.5

A. Steady-state Performance

The steady-state performance is initially investigated for the three comparative schemes. The first test scenario is 10 % rotor speed with a 50 % load torque. As shown in Fig. 8, the smallest torque and current ripples (1.84 Nm and 0.37 A) are obtained by the proposed algorithm. The torque error in the GSMPC is 2.05 Nm, while the value in the effective MPC is 1.96 Nm. The current errors of the GS-MPC and the effective MPC are 0.40 A and 0.38 A. The second test scenario is conducted at the nominal rotor speed with a nominal load torque. The similar performance metrics can be found in Fig. 9. The torque ripples of GS-MPC, effective MPC and the proposed scheme are 2.09 Nm, 2.07 Nm and 1.88 Nm, respectively. Due to more compromises in the vector selection, the ripples in the effective MPC is higher than the proposed algorithm. In the first test scenario, the switching frequencies of the effective MPC and proposed algorithm are 818 Hz and 821 Hz. Owing to lack of effectiveness on switching frequency optimization, a higher switching frequency (845 Hz) is achieved by GS-MPC. In the second test scenario, the switching frequencies of the GS-MPC, effective MPC and the proposed algorithm are 2.82 kHz, 2.77 kHz and 2.77 kHz, respectively. The experimental results on switching frequency validate that the proposed algorithm achieves a similar value of switching frequency with effective MPC, which is lower than that of GS-MPC. The turnaround time of the three algorithms are compared in TABLE. V. The turnaround time of the proposed algorithm is 26 μs. GS-MPC and the effective MPC obtains a longer turnaround time, which is 28 μs and 36 μs, respectively. There are two reasons for a lower turnaround time in the proposed algorithm. First, a fast-sorting algorithm is applied in the proposed cooperative decision-making approach. The least number of comparisons is 10 for each control objective, the highest number of comparisons is 15. The number of comparison is lower than exhaustive search. Second, an adaptive selection mechanism is applied to simplify the circumstances. The number of candidates is only 1 or 2 in proposed algorithm. The optimal is directly obtained by optimizing the switching frequency.

The values of THD are calculated by the collected data of oscilloscope with a s sampling interval and 5000 Hz harmonics. In the first steady state scenario, the IM runs at a 10 % rotor speed with a 50 % load torque. In the first test scenario, the flux THD of GS-MPC, effective MPC and the proposed method are 6.33 %, 8.01 % and 5.94 %, respectively.

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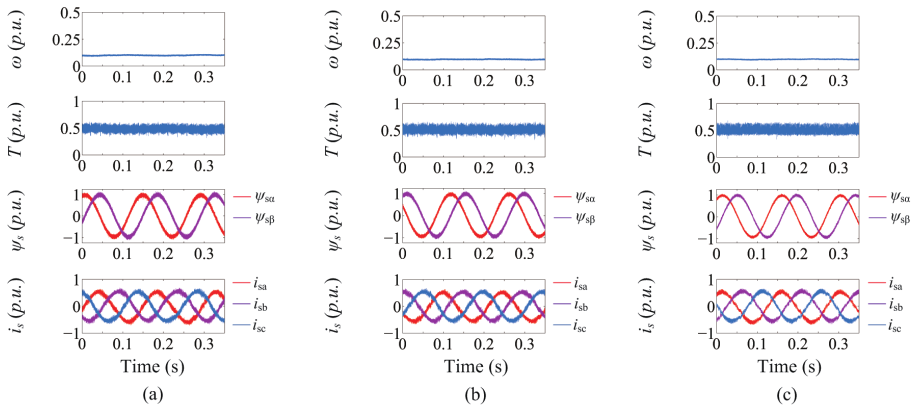

Fig. 8. Stead-state performance at 10 % rotor speed and 50 % load torque. (a) GS-MPC (b) effective MPC (c) proposed cooperative decision-making approach.

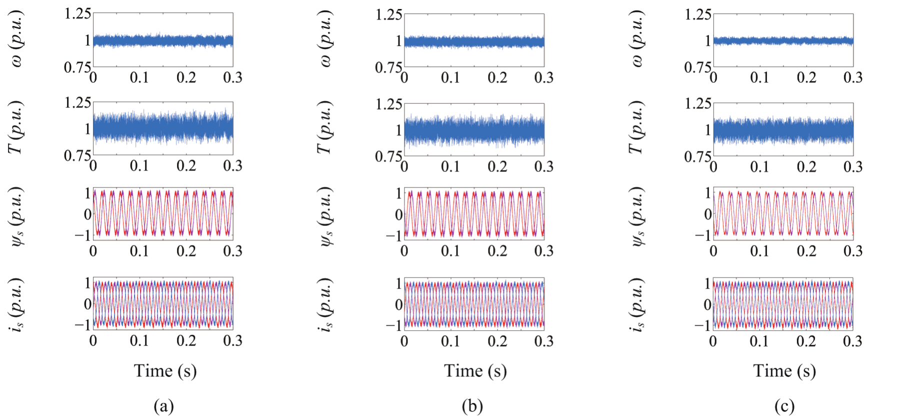

Fig. 9. Stead-state performance at the nominal speed and nominal torque. (a) GS-MPC (b) effective MPC (c) proposed cooperative decision-making approach.

The values of current THD are 11.71 %, 12.91 % and 9.77 %, respectively (see TABLE. III).

TABLE III
STEADY-STATE PERFORMANCE METRICS BETWEEN GS-MPC, EFFECTIVE MPC AND THE PROPOSED ALGORITHM (10 % ROTOR SPEED WITH 50 % LOAD TORQUE)

Algorithms	GS-MPC	effective MPC	proposed
T_{err} [Nm]	2.05	1.96	1.84
i_{serr} [A]	0.40	0.38	0.37
ψ_{sTHD} [%]	6.33	8.01	5.94
i_{sTHD} [%]	11.71	12.91	9.77
f_{sw} [kHz]	0.845	0.818	0.821

In the second test scenario of nominal speed and torque, the values of flux and current THD are compared in TABLE. IV. The flux THD of the three comparative methods are 2.47 %, 3.47 % and 3.21 %, respectively. As shown in TABLE. IV, the current THD of GS-MPC, effective MPC and the proposed algorithm are 7.54 %, 7.94 % and 7.69 %.

The optimization of switching frequency is validated in Fig. 10, which shows the results of the number of candidates in the proposed algorithm. By adjusting the number of collected control inputs in the optimization of flux, the number of common candidates is effectively ranged from 1 to 2. The optimization of switching frequency is taken place between the two candidates, when the number of candidates is 2. It is noteworthy that the possibility of obtaining two candidates is 7/16 in the test scenario of 10 % rated speed with 50 % load torque, while the possibility is 4/16 in the scenario of rated rotor speed and load torque. It is confirmed in Fig. 9 that the switching frequency term is effectively optimized on the basis of a good torque and flux performance.

TABLE IV
STEADY-STATE PERFORMANCE METRICS BETWEEN GS-MPC, EFFECTIVE MPC AND THE PROPOSED ALGORITHM (NOMINAL ROTOR SPEED AND LOAD TORQUE)

Algorithms	GS-MPC	effective MPC	proposed
T_{err} [Nm]	2.09	2.07	1.88
i_{serr} [A]	0.84	0.83	0.79
ψ_{sTHD} [%]	2.47	3.47	3.21
i_{sTHD} [%]	7.54	7.94	7.69
f_{sw} [kHz]	2.82	2.77	2.77

TABLE V
TURNAROUND TIME OF THE COMPARATIVE ALGORITHMS

Algorithms	GS-MPC	effective MPC	proposed
T_{algo} [μs]	28	36	26

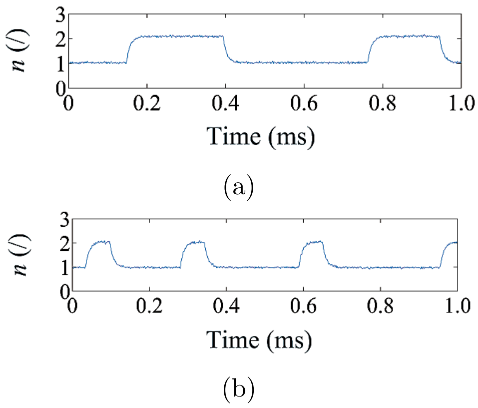

Fig. 10. Collected number of candidate vectors. (a) 10 % rotor speed and 50 % load torque (b) nominal speed and nominal torque.

B. Dynamic Performance

A speed step test is carried out to evaluate the dynamic performance of the proposed algorithm. The IM operates at 50 % rotor speed with a 50 % load torque. At $t = 62\ ms$, a speed step from 50 % to 75 % rotor speed is implemented. As shown in Fig. 11, all the three algorithms show the fast dynamic response that the settling time is 90 ms. The load torque rises to the nominal value in 300 μs. Note that the importance of the multiple objectives is fine-tuned after the transient state. It can be observed that the proposed algorithm obtains a smaller torque ripple. The torque errors of the GS-MPC, effective MPC and the proposed algorithm are 1.90 Nm, 1.66 Nm and 1.53 Nm, respectively. The dynamic performance metrics between GS-MPC, effective MPC and the proposed algorithm are listed in TABLE. VI. The proposed algorithm retains the merit of fast dynamic response of the FCS-MPC schemes. The settling time of rotor speed is 90 ms. The rise time of load torque is 300 μs.

TABLE VI
DYNAMIC PERFORMANCE METRICS BETWEEN GS-MPC, EFFECTIVE MPC AND THE PROPOSED ALGORITHM

Performance metrics	GS-MPC	effective MPC	proposed
T_{err} [Nm]	1.90	1.66	1.53
Settling time [ms]	90	90	90
Torque rise time [μs]	300	300	300

C. Robustness Performance

In the first test scenario, three FCS-MPC methods without weighting factor are compared with a 42 % R_s mismatch (from 2.68 Ω to 3.8 Ω). The IM runs at a nominal speed with a nominal load torque. It is of great importance to optimize the weighting factor in the robustness validation, because parameter mismatch can be considered as a change in the operating condition. It has been investigated in [29] that the conventional FCS-MPC suffers from a weak robustness against R_s mismatch. As shown in Fig. 12, all of the three comparative methods show a strong robustness against R_s mismatch. The reason is that the weighting factors are optimized in all three methods. As shown in TABLE. VII, it is noteworthy that the proposed algorithm obtains a 8.9 % and 33.6 % reduction in the current THD, compared with GS-MPC and effective MPC, respectively.

The second test scenario validates the robustness performance against 88 % R_r mismatch. The rotor resistance increases from 2.13 Ω to 4 Ω. As shown in Fig. 13, the GS-MPC, effective MPC for comparison and the proposed method show a strong robustness against a variation of 88 % R_r. The proposed algorithm shares a similar value of current THD with effective MPC.

TABLE VII
COMPARISONS OF CURRENT THD BETWEEN GS-MPC, EFFECTIVE MPC AND THE PROPOSED ALGORITHM

Current THD [%]	GS-MPC	effective MPC	proposed
42 % R_s mismatch	9.07	12.44	8.26
88 % R_r mismatch	9.33	8.34	8.35

V. CONCLUSION

A cooperative decision-making approach for multi-objective FCS-MPC without the involvement of weighting parameters is proposed in this article. The basic concept behind the proposed algorithm is the decomposition of FCS-MPC optimization problem. Based on the above, a fast-sorting algorithm is applied to collect the results of the decomposed problems. Subsequently, the candidate vectors are obtained by an adaptive mechanism for the master problems. The highlight is the adaptive number of collected results, which leads to a proper number of candidate vectors. The candidate vector which minimizes the switching frequency is regarded as the optimal solution for the multi-objective FCS-MPC problem. Compared with two FCS-MPC schemes without weighting parameters, both the effectiveness and efficiency of the proposed algorithm are experimentally validated on the 2.2 kW IM testbench.

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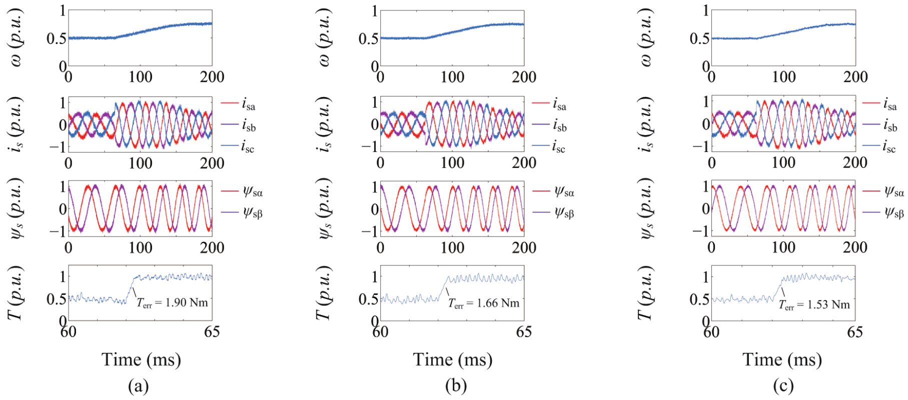

Fig. 11. Dynamic performance from 50 % to 75 % rotor speed with a 50 % load torque. (a) GS-MPC (b) effective MPC (c) proposed cooperative decision-making approach.

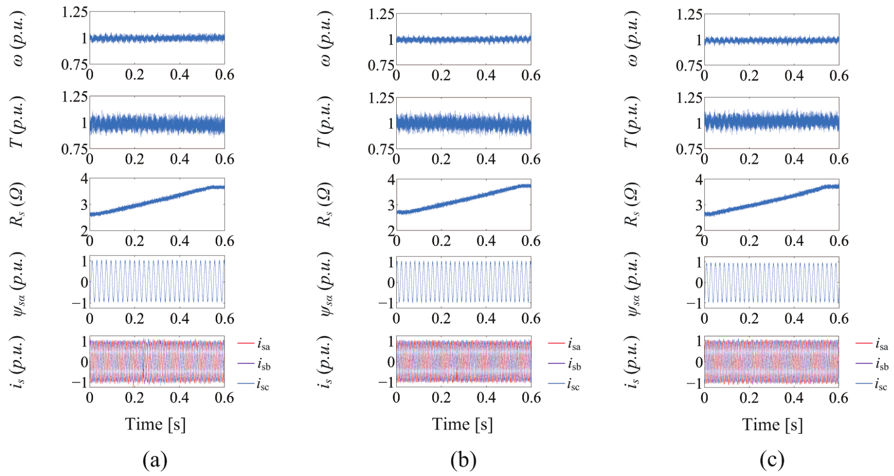

Fig. 12. Comparisons of robust performance with a 42 % R_s mismatch between GS-MPC, effective MPC and the proposed method. (a) GS-MPC (b) effective MPC (c) proposed cooperative decision-making approach.

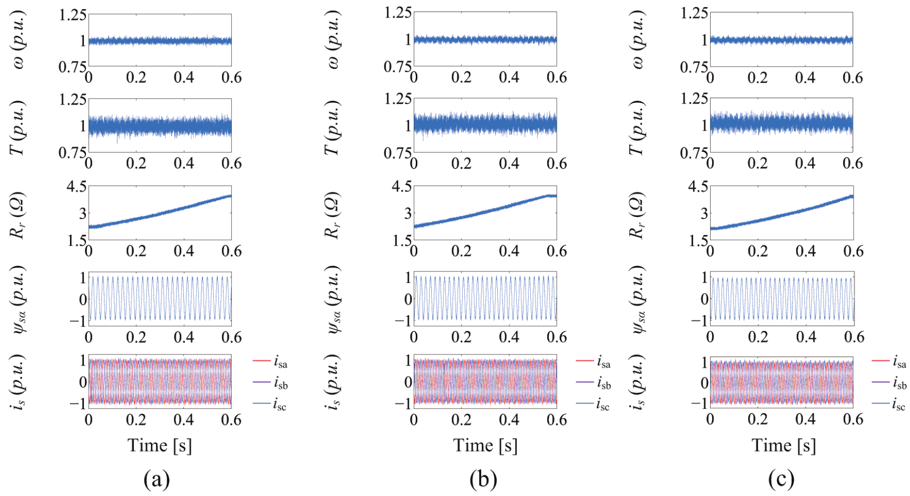

Fig. 13. Comparisons of robust performance with a 88 % R_r mismatch between GS-MPC, effective MPC and the proposed method. (a) GS-MPC (b) effective MPC (c) proposed cooperative decision-making approach.

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