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New Model Predictive Control for Improved Disturbance Rejection

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Abstract: In industrial systems, measurable but controllable disturbances are common and may drive systems away from their references. In standard MPC, its output prediction will have large errors due to these disturbances and thus cause poor regulation performance. In this paper, a complete plant model with disturbance dynamics is considered for better output prediction in MPC so as to improve its regulation. Since unknown future disturbances are also involved, they can be predicted from their past values. To verify its efficiency, a permanent magnet synchronous motor is simulated and shows significant improvement in disturbance rejection in comparison to the integral MPC and classical feedforward control.

Key Words: MPC, regulation control, SQP, Disturbance prediction

1 Introduction

Disturbance influence on process outputs is a crucial issue in most industrial control systems, which usually drives the system away from its operating point and thus control measures are required to eliminate or at least minimize them [1]. In classical control, the feedforward control is a good choice to deal with these disturbances, whose ideal form is formulated as the ratio of dynamics of disturbances to system outputs over the dynamics of control signals to system outputs with a reversed sign [2]. Then disturbances can be perfectly rejected. However, the above ideal compensators are seldom realizable for various reasons, such as their improperness and time lead. Thus, new disturbance rejection strategies are required in practice.

Model predictive control (MPC) is an advanced control technique widely used for disturbance rejection. It optimizes the process in the current timeslot while keeping future timeslots in account [3–6]. Besides, it can handle input constraints easily. Since it always gives optimal control sequence in a finite control horizon but only implements the first one, MPC can plan current control actions with consideration of future events, while other control techniques such as PID and LQR do not have this predictive ability. Besides, its prediction capability can also be used in future disturbance rejection. In practical applications, when some disturbances are measurable, they can be used for better output prediction and therefore better disturbance rejection, which means the disturbance rejection capability of classical MPC technique can be further improved.

MPC has been popular in process control, however, stayed away from fast industrial processes in the past decades for its heavy computation load. Fortunately, with the development in microprocessor, it was not a problem anymore and many researchers had introduced MPC into some typical fast processes, e. g. the power electronics and electrical drives, which has become a hot research topic in recent years. According to literature, the MPC technique had started to handle system disturbances in three main categories, integral MPC, disturbance model and disturbance observer. A constrained model predictive controller was proposed in [7] to regulate the rotating speed of a PMSM based on a linearized state space model. To eliminate the steady state error and the load torque disturbance, an integral action was involved in MPC design. In [8], the nonlinear receding-horizon control was applied on induction motor to achieve asymptotic speed and flux tracking by decoupling them into subsystems, where the integral action was also used to improve its control robustness through handling the unknown time-varying load torque and other mechanical parameter uncertainties. In [9], an explicit nonlinear MPC (ENMPC) was proposed to address the trajectory tracking problem of small-scale helicopter, where an analytical solution is developed based on nominal model and a nonlinear disturbance observer was added to estimate unknown disturbances. In [10], another offset-free MPC was proposed to regulate the output voltage of a three-phase inverter for an uninterruptible power supply, where a disturbance observer was employed to estimate external disturbance and model uncertainties. [11] proposed a predictive controller to deal with measurable disturbances in olive oil mill, where appropriate disturbance models cooperating with MPC can improve the disturbance rejection and trajectory tracking performance. However, it is not an online optimization. [12] used MPC to address the offset-free reference tracking by augmenting the plant model and disturbance model, where its system state and the disturbance were estimated by an observer. However, no disturbance model and prediction were stressed. In [13], unmeasured disturbances were adaptively identified by an auto-regressive model, and then control actions were optimized by classical MPC based on future outputs determined by the identified

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disturbance model and the plant model. [14] proposed an extended generalized predictive control (GPC) to handle measurable disturbances, which demonstrated the classical GPC with implicit disturbance compensation cannot always reject the measureable disturbance. The proposed tuning condition included a reference filter to achieve desired tracking performance and a Filtered Smith Predictor-based structure to improve the control robustness. Most current literature tried to involve estimated disturbance into MPC design through various disturbance observers, but not the predicted disturbances.

In this paper, a new MPC is proposed to provide better regulation on measurable disturbances. We construct a complete plant model with disturbance dynamics, which can produce a better output prediction in MPC to improve its performance. All unknown future disturbances can be predicted from their past values through modeling tools. To verify its efficiency, a permanent magnet synchronous motor (PMSM) is simulated and shows a significant improvement in disturbance rejection in comparison to the integral MPC and the static feedforward control.

The rest of this paper is as follows. The standard MPC principle is introduced in Section II, while the improved MPC strategy with disturbance prediction is in Section III. Section IV presents a simulation study on PMSM speed control. Finally, the paper concludes in Section V.

2 Standard MPC principle

Let the plant be described by

$$\left\{ \begin{array}{l} x\left(k+1\right)=Ax\left(k\right)+Bu\left(k\right), \\ y\left(k\right)=Cx\left(k\right), \end{array} \right. \tag{1}$$

where $x(k)$ is the system state, $u(k)$ the control input and $y(k)$ the system output. Suppose the prediction horizon in MPC design is p. According to the receding horizon principle, the optimal control sequence $U(k)$ is found to drive $Y(k)$ to its reference $\bar{Y}(k)$ by minimizing the cost function $J(k)$,

$$\begin{array}{r} J\left(k\right)=\left(\bar{Y}\left(k\right)-Y\left(k\right)\right)^{T}Q\left(\bar{Y}\left(k\right)-Y\left(k\right)\right) \\ +U^{T}\left(k\right)RU\left(k\right), \end{array} \tag{2}$$

where Q and R are the weighting matrices defined by users, which can be tuned to improve the control performance of MPC. The state and output prediction at time instant k within the prediction horizon p is given by

$$X\left(k\right)=F_{x}x\left(k\right)+G_{x}U\left(k\right), \tag{3}$$

and

$$Y\left(k\right)=F_{y}x\left(k\right)+G_{y}U\left(k\right), \tag{4}$$

respectively, where

$$\begin{array}{l} X\left(k\right)=\left[x\left(k+1\left|k\right.\right),\cdots,x\left(k+p\left|k\right.\right)\right]^{T}, \\ Y\left(k\right)=\left[y\left(k+1\left|k\right.\right),\cdots,y\left(k+p\left|k\right.\right)\right]^{T}, \\ U\left(k\right)=\left[u\left(k\left|k\right.\right),\cdots,u\left(k+p-1\left|k\right.\right)\right]^{T}, \end{array}$$

$$F_{x}=\left[\begin{array}{c} A \\ A^{2} \\ \vdots \\ A^{p} \end{array}\right], G_{x}=\left[\begin{array}{cccc} B & 0 & \cdots & 0 \\ AB & B & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ A^{p-1}B & \cdots & AB & B \end{array}\right],$$

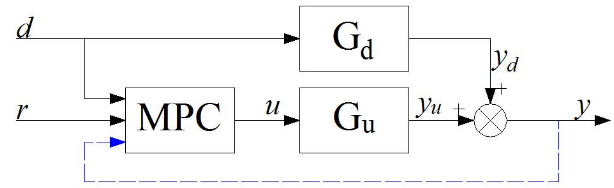

Fig. 1: The improved MPC control scheme with disturbance prediction

$$F_{y}=\left[\begin{array}{c} CA \\ CA^{2} \\ \vdots \\ CA^{p} \end{array}\right], G_{y}=\left[\begin{array}{cccc} CB & 0 & \cdots & 0 \\ CAB & CB & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ CA^{p-1}B & \cdots & CAB & CB \end{array}\right].$$

Substituting Eqn.(4) into Eqn.(2) and omitting its constant terms gives an equivalent cost function,

$$\begin{array}{r} \bar{J}(k)=U^{T}(k)(G_{y}^{T}QG_{y}+R)U(k) \\ -2(\bar{Y}(k)-F_{y}x(k))^{T}QG_{y}U(k). \end{array} \tag{5}$$

In practical application, various constraints arise from limitations of electrical and mechanical capabilities. Specifically for a motor, the magnitudes of control inputs or their increments should be within the motor limits. These constraints can be categorized into equality ones and inequality ones and further defined as follows,

$$U_{\min}\le U\left(k\right)\le U_{\max}, \tag{6}$$

and

$$X_{\min}\le X\left(k\right)\le X_{\max}. \tag{7}$$

Eqn.(5) to Eqn.(7) assemble a standard Sequential Quadratic Programming (SQP) problem with constraints, which can be iteratively solved through the existing algorithms [15].

3 New MPC with disturbance prediction

Disturbance is inevitable in most industrial processes, which usually has negative impact on their system stability and reference tracking. Fortunately, some disturbances are measurable with explicit dynamics to system outputs. Thus, they can be employed in MPC design as shown in Fig.1 to improve its disturbance rejection performance.

Suppose that the system model with disturbance dynamics is

$$\left\{ \begin{array}{l} x\left(k+1\right)=Ax\left(k\right)+Bu\left(k\right)+B_{d}d\left(k\right), \\ y\left(k\right)=Cx\left(k\right), \end{array} \right. \tag{8}$$

where $d(k)$ is the measurable disturbance. Then the state and output prediction at time instant k within its prediction horizon p becomes

$$X\left(k\right)=F_{x}x\left(k\right)+G_{x}U\left(k\right)+H_{x}D\left(k\right), \tag{9}$$

and

$$Y\left(k\right)=F_{y}x\left(k\right)+G_{y}U\left(k\right)H_{y}D\left(k\right), \tag{10}$$

where

$$D(k)=[d(k),\cdots,d(k+p-1)]^{T},$$

$$H_x = \begin{bmatrix} B_d & 0 & \cdots & 0 \\ AB_d & B_d & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ A^{p-1}B_d & \cdots & AB_d & B_d \end{bmatrix},$$

$$H_y = \begin{bmatrix} CB_d & 0 & \cdots & 0 \\ CAB_d & CB_d & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ CA^{p-1}B_d & \cdots & CAB_d & CB_d \end{bmatrix}.$$

Then the cost function in Eqn.(5) for receding horizon optimization becomes

$$\begin{aligned} \bar{J}(k) = {} & U^T(k)\left(G_y^T Q G_y + R\right)U(k) \\ & -2\left(\bar{Y}(k) - F_y x(k) - H_y D(k)\right)^T Q G_y U(k), \end{aligned} \tag{11}$$

where another standard SQP problem is formed by Eqn.(6), Eqn.(7) and Eqn.(11) and therefore can be iteratively solved through the same algorithms.

Through disturbance $d(k)$ can be measured at time instant k, its future values, $\{d(k+1), ..., d(k+p-1)\}$, are unknown, which need to be estimated. In this paper, two methods are considered to deal with future disturbances, where they are explicitly known in the first method, while are predicted through polynomial extrapolation approach in the second method.

The extrapolation is to estimate the future function value based on the prior knowledge of the existing data. It usually fits the latest data points to a polynomial function and uses the function to estimate future outcomes beyond the end of known data. Suppose a q-order polynomial function as

$$d(k) = \alpha_0 + \alpha_1 k + \cdots + \alpha_q k^q + \varepsilon, \quad k \geq q+1, \tag{12}$$

where ε is the fitting error. Its parameters, $[\alpha_0, \alpha_1, \cdots, \alpha_q]$, can be determined by N known data with $N \geq q+1$ through the least square techniques. Then it is extended beyond the end of known data for prediction, which is

$$\begin{aligned} \hat{d}(k+i) = \alpha_0 + \alpha_1(k+i) + \cdots + \alpha_q(k+i)^q, \\ k \geq q+1, 1 \leq i \leq p, \end{aligned}$$

where i is the leading intervals to the end of known data. However, the above method does not work at $k \leq q$ as there are not enough data points to build the polynomial function in Eqn.(12). In our simulation, we use the latest $d(k)$ as the values of its future prediction, which is

$$\hat{d}(k+i) = d(k), \quad k \leq q, \quad 1 \leq i \leq p.$$

According to the Runge's phenomenon, a higher degrees of polynomial does not always improve the extrapolation accuracy. This is verified in our simulations and therefore the first-order linear extrapolation is adopted here. Besides, N is an important design parameter in extrapolation. A larger N results in less fluctuation but slower reaction in prediction period, while smaller N results in more fluctuation but faster reaction.

Let us turn to stability of the proposed control scheme. The MPC solves an online receding horizon optimal control problem and its main difference from the classical control with a pre-computed control law is that it yields an optimal control sequence through SQP by using its current state as the initial state while only the first control action is applied. But as stated in [16], optimality does not imply stability. In the literature, the Lyapunov stability theory has become an universal method for stability analysis of MPC. The value function for the receding horizon optimization was used in [17] as the Lyapunov function. Augmented with the terminal equality constraint, the stability of MPC was analysed [4]. However, such a constraint is too restricted to meet and therefore may result in no solution, especially for a system with disturbance. Thus, the terminal equality constraint is usually released to the terminal cost function or terminal constraint set. Our stability analysis here follows this framework.

For system at state $x(k)$, the cost function in Eqn.(2) is extended to infinite horizon by adding the terms after $k+p$, which becomes

$$J_p(k) = \sum_{i=0}^{p-1} g(x(k+i|k), u(k+i|k)) + F(x(k+p|k)), \tag{13}$$

where $g(x(k), u(k))$ is the stage cost at k while

$$F(x(k+p|k)) = \sum_{i=p}^{\infty} g(x(k+i|k), u(k+i|k)), \tag{14}$$

is its cost function after $k+p$. Obviously, the value of $F(x(k+p|k))$ relates closely to its control strategy after $k+p$, which actually is not implemented in MPC but affects its stability. Suppose a local controller $\kappa_c(x)$ can exponentially stabilize the system after it being into the terminal constraint set X_f.

Let the optimal control sequence at time instant k be

$$U^*(k) = \{u^*(k|k), \cdots, u^*(k+p-1|k)\},$$

and its resultant optimal state trajectory be

$$X^*(k) = \{x^*(k+1|k), \cdots, x^*(k+p|k)\}.$$

Then the minimized cost function at $t = k$ is

$$\begin{aligned} J_p^*(k) = {} & \textstyle\sum_{i=0}^{p-1} g(x^*(k+i|k), u^*(k+i|k)) \\ & +F(x^*(k+p|k)), \end{aligned} \tag{15}$$

At time instant k+1, the MPC control sequence $u^*(k|k)$ steers the system to $x^*(k+1|k)$. Then a feasible solution is

$$U(k+1) = \{u(k+1|k+1), \cdots, u(k+p|k+1)\},$$

where $u(k+i|k+1) = u^*(k+i|k)$ at $1 \leq i \leq p-1$ and $u(k+p|k+1) = \kappa_c(x^*(k+p|k))$. Its new trajectory is

$$X^*(k) = \{x^*(k+2|k), \cdots, x(k+p+1|k)\},$$

and the cost function is

$$\begin{aligned} J_p(k+1) = {} & \textstyle\sum_{i=1}^{p} g(x^*(k+i|k), u^*(k+i|k)) \\ & +F(x^*(k+p+1|k)), \end{aligned} \tag{16}$$

Thus, it follows

$$\begin{aligned} J_p^*(k) - J_p(k+1) = {} & g(x^*(k|k), u^*(k|k)) \\ & +F(x^*(k+p|k)) \\ & -g(x^*(k+p|k), u^*(k+p|k)) \\ & -F(x^*(k+p+1|k)). \end{aligned} \tag{17}$$

Since the sum of four terms in right side of Eqn.(17) is no less than zero, $J_p(k+1) \leq J_p^*(k)$. Moreover, the control sequence $U(k+1)$ at $k+1$ is one of feasible solutions, its optimal one $U^*(k+1)$ at $k+1$ would perform no worse than it and therefore we have

$$J_p^*(k+1) \leq J_p(k+1) \leq J_p^*(k), \tag{18}$$

which means that the proposed MPC strategy is asymptotically stable. Since the control signal and system state are under constraints, the system may not meet the terminal constraint set X_f within its prediction horizon. Suppose that the state $x(k)$ can be driven into X_f within m time instants. The cost function after $k+p$ becomes

$$\begin{aligned} F(x(k+p|k)) = &\textstyle\sum_{i=p}^{m-1} g(x(k+i|k), u(k+i|k)) \\ &+F(x(k+m|k)). \end{aligned} \tag{19}$$

Then the stability of the proposed MPC under the constraints can also be shown with Eqn.(19) similarly to the case with Eqn.(14).

4 Simulation Studies

The PMSM drives are widely used in industrial applications owing to their size, low cost, simple structure and high power density [18]. However, they represent a highly coupled and nonlinear multivariable system and therefore perform poorly with open-loop scalar V/Hz control as no rotor coil provides mechanical damping in transient conditions [19]. Additionally, Field-oriented Control is another popular control technique with PMSM drives [20, 21]. However, the above classical control techniques cannot deal with system disturbance efficiently.

4.1 The PMSM model in $d-q$ frame

The permanent magnet synchronous motors are widely used in various industrial processes for their high efficiency and dynamic performance. Based on the well-known $d-q$ rotating reference frame [18], its dynamics can be described by

$$\begin{cases} \frac{di_d}{dt} = \frac{1}{L_d}(V_d - Ri_d + \omega_e L_q i_q), \\ \frac{di_q}{dt} = \frac{1}{L_q}(V_q - Ri_q - \omega_e L_d i_d - \omega_e \phi_{mg}), \\ \frac{d\omega_e}{dt} = \frac{1}{J}(pT_e - f\omega_e - pT_L), \\ T_e = \frac{3}{2}p(\phi_{mg} i_q + (L_d - L_q) i_d i_q), \end{cases} \tag{20}$$

where its variables notation and technical parameters of PMSM are summarized in Table 1. For control of a PMSM,

Table 1: The variables notation of PMSM model

Notation	Description	Value
J	The moment of inertia of PMSM	$2.35 \times 10^{-4} kg \cdot m^2$
f	Viscous coefficient	1.1×10^{-4}
L_d, L_q	d-q axis inductance	$7 \times 10^{-3} H$
R	Stator resistance	2.98Ω
ϕ_{mg}	Rotor flux	$0.125Wb$
p	Number of pole pairs	2
V_d, V_q	Stator voltages in d-q frame	
i_d, i_q	Stator currents in d-q frame	
ω_e, ω_m	Electrical speed and rotor speed	$\omega_e = p \times \omega_m$
T_e, T_L	Electromagnetic and load torques	

the reference of d-axis current is set to zero for energy efficiency. Besides, $i_d = 0$ allows the electromagnetic torque T_e controlled by i_q directly. For any surface mounted PMSM, its inductance of $d-q$ axis satisfies $L_d = L_q$ in practical applications. Thus, its electromagnetic torque T_e can be simplified as

$$T_e = \frac{3}{2} p \phi_{mg} i_q.$$

In PMSM speed control, one major disturbance is the external load torque T_L applied on motor shaft, whose dynamics is also in Eqn. (20). Besides, the PMSM state variables in d-axis and q-axis are cross-coupled. For convenience in MPC design, the nonlinear system in Eqn.(20) is linearized at an operating point i_{d0}, i_{q0}, ω_{e0} and the linearized model is

$$\begin{cases} \dot{x} = Ax + Bu + Fd, \\ y = Cx, \end{cases} \tag{21}$$

where $x = [i_d, i_q, \omega_e]^T$, $u = [V_d, V_q]^T$, $d = T_L$ and $y = [i_d, \omega_e]^T$,

$$A = \begin{bmatrix} -\frac{R}{L_d} & \frac{L_q \omega_{e0}}{L_d} & \frac{L_q i_{q0}}{L_d} \\ -\frac{L_d \omega_{e0}}{L_q} & -\frac{R}{L_q} & -\frac{L_d i_{d0} + \phi_{mg}}{L_q} \\ 0 & \frac{3p^2 \phi_{mg}}{2J} & \frac{-B_v}{J} \end{bmatrix},$$

$$B = \begin{bmatrix} \frac{1}{L_d} & 0 \\ 0 & \frac{1}{L_q} \\ 0 & 0 \end{bmatrix}, F = \begin{bmatrix} 0 \\ 0 \\ -\frac{p}{J} \end{bmatrix}, C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

Since a discrete model is required in MPC design, the continuous state space model in Eqn.(21) is discretized with sampling time T_s and the resulting discrete state space model is given by

$$\begin{cases} x(k+1) = A_d x(k) + B_d u(k) + F_d d(k), \\ y(k) = C_d x(k), \end{cases} \tag{22}$$

where $A_d = e^{AT_s}$, $B_d = \int_0^{T_s} e^{A\tau} B d\tau$, $F_d = \int_0^{T_s} e^{A\tau} F d\tau$, $C_d = C$.

4.2 References and disturbances

In speed control of PMSM, its d-axis current is expected to be zero for energy efficiency [7]. Thus, the control target of proposed MPC strategy is tracking the electrical speed reference while keeping zero current in d-axis through adjusting the stator voltages V_d and V_q in the $d-q$ frame. In our simulation studies, two output references are set as $i_d = 0$, $\omega_e = 100\ rad/s$, respectively. Without loss of generality, three typical disturbance types, the trapezoidal wave disturbance and the sawtooth wave disturbance are used in simulation. The first-order polynomial extrapolation with $N = 5$ is adopted to predict disturbances within the MPC prediction horizon.

4.3 Benchmark methods

In comparison to the proposed method, the classical MPC strategy with integral action in [7] is allocated as the benchmark method, whose main idea is transferring Eqn.(22) into incremental form,

$$\delta x(k+1) = A_d \delta x(k) + B_d \delta u(k), \tag{23}$$

and augmenting them into a new model,

$$\begin{cases} \begin{bmatrix} \delta x(k+1) \\ x(k+1) \end{bmatrix} = \begin{bmatrix} A_d, 0 \\ A_d, I \end{bmatrix} \begin{bmatrix} \delta x(k) \\ x(k) \end{bmatrix} + \begin{bmatrix} B_d \\ B_d \end{bmatrix} \delta u(k), \\ y(k) = [0, C_d][\delta x(k), x(k)]^T. \end{cases} \tag{24}$$

Table 2: Comparison of three control strategies

		Static Feedforward		Integral MPC		The Proposed MPC	
Disturbance	Measures	IAE	MAE	IAE	MAE	IAE	MAE
Trapezoidal	i_d	0.0048	0.0644	0.0088	0.1217	0.0025	0.0430
	ω_e	0.5852	7.2504	0.1851	2.6258	0.0544	0.8915
Sawtooth	i_d	0.0058	0.0412	0.0160	0.0505	0.0027	0.0283
	ω_e	1.0127	2.9556	0.3307	1.2581	0.0373	0.6375

Then classical MPC is designed based on the new model in Eqn.(24) for disturbance rejection.

Additionally, the static feedforward control is also used as a benchmark. Suppose that the PMSM drive in Eqn.(20) stabilizes at ω_{e0} under load torque T_L. Its steady control inputs should be

$$\left\{ \begin{array}{l} V_d = -\omega_{e0} L_q i_q, \\ V_q = R i_q + \omega_{e0} \phi_{mg}, \end{array} \right. \tag{25}$$

where

$$i_q = \frac{2(f\omega_{e0} + pT_L)}{3p^2 \phi_{mg}}.$$

4.4 Performance measures

To evaluate the disturbance rejection performance, two performance measures are defined for our simulation study, which are the integral absolute error (IAE),

$$IAE = T_s \sum\nolimits_{k=1}^{n} \left| \bar{y}(k) - y(k) \right|, \tag{26}$$

and the maximum absolute error (MAE),

$$MAE = \max \left| \bar{y}(k) - y(k) \right|, \quad k = 1, \cdots, n, \tag{27}$$

respectively, where $y(k)$ and $\bar{y}(k)$ are system outputs and its references.

4.5 Results and Discussion

Three control schemes are shown in Fig.2 and Fig.3 for disturbance transient responses. The performance measures are calculated and exhibited in Table 2. One sees that the proposed MPC strategy with disturbance prediction performs much better than two benchmark methods. Actually, two benchmark methods cannot eliminate steady state errors when the disturbance is varying.

5 Conclusions

In this paper, an improved disturbance rejection control scheme based on MPC technique has been proposed. The main idea is that the disturbance is predicted based on its measurements up to now, and the predicted disturbance is further used to predict the process output so that the output prediction can be much more accurate in presence of disturbance in comparison with the standard MPC where the disturbance can only be asymptotically rejected. Stability analysis is provided for the proposed scheme. The proposed method is benchmarked against two popular and relevant methods on PMSM speed control, for different disturbance types, and it performs much better in disturbance rejection than other methods.

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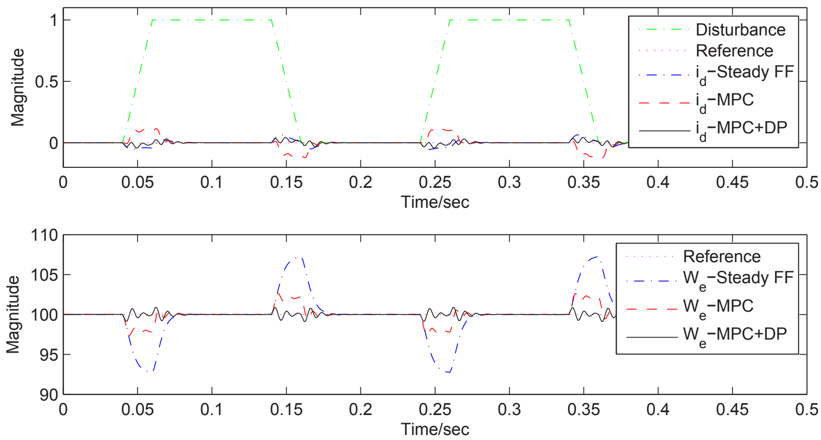

Fig. 2: System outputs comparison under trapezoidal wave disturbance

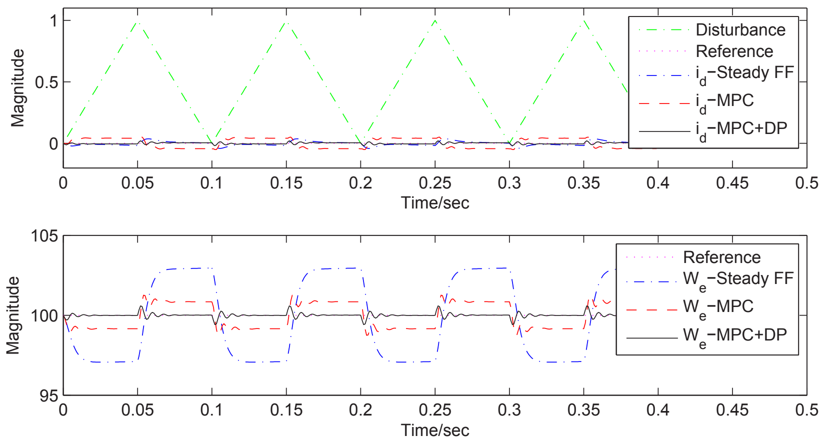

Fig. 3: System outputs comparison under sawtooth wave disturbance

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