International Journal of Industrial Electronics, Control and Optimization © 2021 IECO
Vol. 4, No. 1, pp. 87-98, Jan (2021)

Cooperative Distributed Constrained Model Predictive Control for Uncertain Nonlinear Large-Scale Systems

Ahmad Mirzaei[1], and Amin Ramezani[2,†]

[1,2] Center of Advanced Control Systems, School of Electrical and Computer Engineering, Tarbiat Modares University, Tehran, Iran

ABSTRACT

In this paper, two linear constrained cooperative distributed extended dynamic matrix control (CDEDMC) and adaptive generalized predictive control (CDGPC) are proposed to control the uncertain nonlinear large-scale systems. In these approaches, a proposed cooperative optimization is employed which improves the global cost function. The cost values and convergence time are reduced using the proposed cooperative optimization strategy. The proposed approaches are designed based on the compensation of the mismatch between linearized and nominal nonlinear models. In CDEDMC the mismatch is considered as a disturbance and compensated; Also in CDGPC, it is compensated using online identification of the linearized model. The typical distributed linear algorithms like DMC leads to an unstable response if the reference trajectory is a little far from the equilibrium point. This problem will be partially solved using the CDEDMC and will be completely solved using the CDGPC even if the reference trajectory is too far from the equilibrium point. The performance and effectiveness of proposed approaches are demonstrated through simulation of a typical uncertain nonlinear large-scale system.

Article Info

Keywords:
Cooperative distributed extended dynamic matrix control, Cooperative distributed adaptive generalized predictive control, Cooperative optimization approach.

Article History:
Received 2020-04-25
Accepted 2020-10-02

I. Introduction

Distributed model predictive control (DMPC) is one of the most appropriate and practical approaches for dealing with uncertain nonlinear large-scale systems, which are a major part of industrial systems. Linear DMPC approaches are divided into two categories in terms of how the subsystems interconnect with each other in the optimization process; cooperative and non-cooperative, both of which could be implemented in nonlinear large-scale systems [1]. In dual-mode DMPC methods, based on the displacement of the states from the origin, the DMPC algorithm changes from the linear algorithm to a nonlinear one or vice versa. When the states are in the neighborhood of the origin, the linear DMPC algorithm is applied and vice versa, when they are far from the origin, the nonlinear algorithm is applied. The main advantage of dual-mode methods is that the complexity is reduced in comparison with fully nonlinear algorithms. However, the main disadvantage of these methods is that the convergence time and the probability of errors in the optimization process are increased compared to fully linear or nonlinear methods [2]. Some large-scale systems require the coordination layer in their optimization process, depending on their control objectives and the interaction between their local controllers [3, 4, and 5]. The advantage of coordination based methods is that they allow full interconnection between subsystems. However, the disadvantages of these methods are that they add a layer to the design and increase the likelihood of optimization errors and also increase the complexity of the design. On the other hand, in some other large-scale systems, the mentioned goals are provided by alternative methods like the Gradient Projection method, without the need for a coordinator layer [6, 7]. The interconnections between local controllers could be considered as constraints in their

†**Corresponding Author**: ramezani@modares.ac.ir
Tel: +982182883592, Fax: +982182884325, Tarbiat Modares University. Center of advanced Control systems, School of Electrical and Computer Engineering, Tarbiat Modares University, Tehran, Iran.

optimization process instead of applying the coordination layer. The advantage of this approach is that it is proper and applicable for weakly coupled large-scale systems [8, 9]. The most important concern in methods that use the coordination layer in the optimization process or methods that each subsystem computes its own optimal control separately and then dispatches to its neighboring subsystems is communication delay. Most of these methods take this communication delay as a constraint [10]. Robust DMPC approaches are useful for constrained large-scale systems. One of these robust approaches is designed based on the two-layer robust method. In this method, each local controller receives control information of its neighboring subsystems and calculates its own optimal control. In the first layer, the recursive feasibility of convergence of whole system states is presented. A robust DMPC algorithm is applied in the second layer [11, 12]. The main advantage of robust approaches is that the inherent constraints of the system can be considered and taken into account in the optimization process. However, the main disadvantages of these approaches are their high cost and long convergence time. The Sequential DMPC approach is another useful strategy for constrained nonlinear large-scale systems. In this strategy, each local controller computes its own optimal control and dispatches to its neighbors via the communication channel to obtain the global optimality [13, 14]. The coupling between subsystems can be invigorated and also sampling intervals can be larger via applying contraction theory in DMPC approaches [15, 16]. The main disadvantage of sequential approaches is that they increase the convergence time.

DMPC approaches based on hierarchical strategy are practical methods for uncertain large-scale systems. These methods consider the inaccurate information of the actuators of the large-scale system and are designed at two levels. The faults of actuators are retrieved to retain the design specifications of all subsystems at the first level. The retrieval process is applied by enhancing the performance of the system at the second level. The developed hierarchical DMPC satisfies the retrieval design specifications by lower fault compensation. Thus, the cost is reduced in comparison with centralized and decentralized strategies [17, 18].

The linear and nonlinear constrained DMPC approaches could be applied to uncertain nonlinear large-scale systems. If a nonlinear large-scale system can be controlled using a linear distributed controller, it is rational to use linear methods because of their less complexity. The design complexity and cost in the linear DMPC approaches are less than nonlinear approaches [19, 20]. If the nonlinear large-scale system has a high degree of nonlinearity, then there may be limitations for applying the linear algorithms.

The contribution of this paper is that a novel CDMPC algorithm is proposed which decreases the complexity of optimization, cost values, and convergence time. Moreover, two reconstructed linear algorithms are proposed based on Dynamic Matrix Control (DMC) and Generalized Predictive Control (GPC) methods to profit from the advantages of linear DMPC approaches to control the uncertain nonlinear large-scale systems. If the reference trajectory deviates too close to the equilibrium point then the nonlinear system could be controlled by linear algorithms. However, there are many nonlinear industrial plants with a high degree of nonlinearity which could not be controlled using linear algorithms like DMC. Moreover, if the reference trajectory deviates farther away from the equilibrium point, these plants may be unstable. These problems will be solved using the proposed cooperative distributed linear algorithms in this paper; Cooperative Distributed Extended Dynamic Matrix Control (CDEDMC) and Cooperative Distributed Adaptive Generalized Predictive Control (CDGPC).

The remainder of the paper is organized as follows. In section 2, the problem statement for nonlinear interconnected large-scale systems is given. In section 3, the new cooperative optimization approach is proposed. The reconstructed distributed model predictive controllers are proposed in section 4. Section 5, presents the simulation results for a typical nonlinear large-scale system. Finally, concluding remarks are expressed in section 6.

II. Mathematical Model of Nonlinear Large-Scale Systems

A typical nonlinear large-scale system is considered which consists of M interconnected subsystems. The nonlinear dynamic of subsystem i is described by the following input-output implementation:

$$\dot{y}_i(t) = f_i\left(y_i, u_i, u_j\right), \qquad i = 1,2, \dots, M \tag{1}$$

where $y_i \in R^{n_{y_i}}$ and $u_i \in R^{n_{u_i}}$ present the vectors of outputs and inputs of subsystem i respectively and $u_j(t)$ $(j = 1,2, \dots, M, j \neq i)$ is the vector of inputs of the subsystem j which is the neighboring subsystem of subsystem i. f_i is a nonlinear Lipschitz function. The M sets of control inputs are constrained to be in M convex sets, $U_i \subset R^{M_{u_i}}, i = 1, \dots, M$ which are expressed as:

$$U_i = \{u_i \in R^{n_{u_i}} : \ |u_i| \leq u_i^{Max}\} \tag{2}$$

where $u_i^{Max}, i = 1, \dots, M$ are the magnitudes of constraints of the inputs.

The continuous-time nonlinear model of subsystem i in (1) is discretized by applying Euler derivative approximation with sampling time T_s:

$$y_i(k+1) = g_i\left(y_i(k), u_i(k), u_j(k)\right), i = 1,2, \dots, M \tag{3}$$

where, g_i is also a nonlinear function. In the present paper, a new cooperative optimization approach is proposed. Moreover, two reconstructed distributed linear constrained algorithms; CDEDMC and CDGPC, are proposed to employ the proposed cooperative optimization approach and control the nominal uncertain nonlinear large-scale system in (1).

III. Proposed Cooperative Optimization Approach

According to the interconnection protocol of local controllers in large-scale systems, DMPC approaches are classified into two main categories, cooperative and non-cooperative. In cooperative methods unlike the non-cooperative ones, and in each local controller the global cost function, which is a combination of cost functions of all subsystems, is optimized to investigate the effect of each optimal control input on the whole system. In this approach, each control input is optimized in the corresponding local controller via optimizing the global cost function assuming that the control inputs of other subsystems are fixed to their optimal values of the previous iteration [1, 21]. The aforementioned global cost function is modified in the proposed CDMPC which is redefined as a convex combination of its own and its neighboring subsystems' cost functions instead of all other subsystems' cost functions. Therefore, the proposed CDMPC approach in this manuscript supposes that, if according to Equ. 1, two nominal subsystems are not neighbors to each other, then their local cost functions are not included in each other's global cost functions. The complexity and computational burden of optimization are reduced using the proposed approach. The proposed CDMPC approach applies the following cooperative strategy:

1. At time k, all local controllers receive the information of the whole large-scale system in (3).
2. At iteration c:

2.1. Each subsystem i computes its own future input vector U_{+_i} along the assigned control horizon based on the input vectors of its neighboring subsystems which are fixed to their optimal vectors of previous iteration $c-1$.

2.2. All neighboring subsystems dispatch their input vectors to each other and each local controller i computes the current iteration optimal vector $U_i^{Opt^c}$.

2.3. Based on receding horizon criteria, the current iteration optimal control $u_i^{Opt^c}$, is the first component of the current iteration optimal vector $U_i^{Opt^c}$.

3. If the termination error condition which is taken into account in the global cost function is satisfied, each subsystem i exchanges its optimal control $u_i^{Opt^c}$ to its actuators; if not satisfied, go back to step 2 and let $c+1 \to c$.
4. The models of subsystems are updated using achieved corresponding optimal controls.
5. Whenever the control inputs of all local controllers are obtained, go back to the first step and let $k+1 \to k$.

The local controller i solves the following proposed optimization problem at each iteration c:

$$\min_{\Delta u_i(k),\dots,\Delta u_i(k+m-1)} J(k) \quad U_i = [\Delta u_i(k) \dots \Delta u_i(k+m-1)]^T \tag{4}$$

Subject to Equ. 3.

$$u_i(k+j) \in U_i, j = 0, \dots, m-1 \tag{5}$$

$$U_l^c = U_l^{c-1}, \forall l \in L \text{ and } l \neq i \tag{6}$$

$$\|\hat{y}_i(\tau) - W(\tau)\|_{Q_i}^2 \in \frac{p}{\tau-(k-1)} y_t, \tau \in [k, k+p] \tag{7}$$

with:

$$J(k) = \alpha_i J_i + \sum_l \alpha_l J_l \tag{8}$$

$$\alpha_i, \alpha_l > 0, \alpha_i + \sum_l \alpha_l = 1 \tag{9}$$

and:

$$J_i(k) = \sum_{j=1}^{p} \left[\|\hat{y}_i(k+j) - W(k+j)\|_{Q_i}^2\right] + \sum_{j=1}^{m} \|\Delta u_i(k+j-1)\|_{R_i}^2 \tag{10}$$

where m and p are control and prediction horizons respectively, $L \subset M$ is the set of neighbors of subsystem i. Equ. 7, denotes the termination error condition in which y_t is the symmetric closed set in the neighborhood of origin. The termination error condition expresses that if the system is closed-loop stable, then the prediction error goes to zero. $\hat{y}_i(k+j), j = 1, \dots p$ is the subsystem's i predicted output that in each linear MPC algorithm is computed via a special method. W denotes the reference trajectory. Q_i and R_i are positive definite diagonal weighting matrices of prediction errors and control inputs respectively. $J(k)$ is presented as a convex combination of cost functions subsystem i and its neighbors with convenient α_i and α_l coefficients to obtain global optimality.

IV. Proposed Constrained CDMPC Approaches

The application of linear algorithms to control nonlinear systems has been proposed in many methods for two main reasons. First, according to experimental data, a linear system is much easier identified than a nonlinear system. Second, most practical nonlinear systems like liquid level control, pressure control, and temperature control of a furnace just have one equilibrium point, so they can be identified by an accurate linear first-order model, and then linear DMPCs can be employed to control the linearized system and determine the optimal controls of subsystems.

In this manuscript, two reconstructed constrained cooperative distributed linear algorithms; CDEDMC and CDGPC are proposed to control the nonlinear uncertain large-scale systems. These algorithms are distinguished via how the nonlinear model is applied in the optimization process. In CDEDMC the linearized version of the nominal nonlinear model is applied and the mismatch between linearized and nonlinear models is considered as a constraint and will be compensated. So the predicted outputs calculated via both models are similar to each other. The CDGPC algorithm identifies the numerator and denominator polynomials of the transfer function of the linearized model which indeed provides the nonlinear dynamics of the system.

A. Proposed Constrained CDEDMC Approach

In fact, EDMC is the extended version of the DMC algorithm that takes the nonlinear model into account, so this algorithm also uses the system's step response to determine the predicted outputs similar to DMC [22].

The predicted output of the subsystem i in distributed DMC algorithm is represented as follows:

$$\hat{y}_i(k+j)=\sum_{q=1}^{N} g_{iq}\Delta u_i(k+j-q) + \sum_{l}\sum_{q=1}^{N} g_{ilq}\Delta u_l(k+j-q) + \hat{n}_i(k+j), i=1,\dots,M, l\in L, l\neq i \tag{11}$$

where g_{iq} and g_{ilq} are the step responses coefficients of subsystem i and its interconnected neighboring subsystem l, N is the model horizon, and Δu_i and Δu_l are the increment control inputs of subsystems i and l respectively. An integrator should be added to remove the steady-state error so increment of control inputs are used instead of control input in DMC and so in EDMC methods. $\hat{n}_i(k+j)$ is the estimation of the future time disturbances assuming that disturbance and other signals of plant, until time j, are presented. In distributed DMC, $\hat{n}_i(k+j)$ is considered as external disturbances applied to the system. Moreover, it is assumed that the future disturbance is constant along the prediction horizon and equal to the current disturbance $\hat{n}_i(k)$. The disturbance is defined as the difference between measured and predicted outputs:

$$\hat{n}_i(k+j)=\hat{n}_i(k)=y_{m_i}(k)-\sum_{q=1}^{N} g_{iq}\Delta u_i(k-q) - \sum_{l}\sum_{q=1}^{N} g_{ilq}\Delta u_l(k-q) \tag{12}$$

where the $y_{m_i}(k)$ is the measured output. The cost function of subsystem i in distributed DMC is:

$$J_i(k)=\sum_{j=1}^{p}\|\hat{y}_i(k+j)-W(k+j)\|_{Q_i}^2 + \sum_{j=1}^{m}\|\Delta u_i(k+j-1)\|_{R_i}^2 \tag{13}$$

and also the cost function is represented as the matrix form of:

$$J_i=(Y_i-W)^T Q_i (Y_i-W)+{U_i}^T R_i U_i \tag{14}$$

in which elements of the Y_i are obtained using Equs. 11-12 and series characteristics:

$$Y_i=G_i U_i+\sum_{l\neq i} G_{il}U_l + Free\ Response_i \tag{15}$$

$$Free\ Response_i = H_i U_{-i}+\sum_{l\neq i} H_{il}U_{-l}+y_{m_i}I_{p\times 1} \tag{16}$$

where Y_i is the predicted outputs vector, U_{+_i} and U_{+_l} are the future control input vectors, and U_{-_i} and U_{-_l} are the determined past control input vectors of subsystems i and l respectively. According to the cooperative optimization approach proposed in section 3 the future control inputs vector of neighboring subsystem l in iteration c is constant and equal to its latest optimal value. G_i,G_{il},H_i, and H_{il} are MPC matrices with appropriate dimensions:

$$Y_i=\begin{bmatrix}\hat{y}_i(k+1)\\ \vdots\\ \hat{y}_i(k+p)\end{bmatrix}, U_i=\begin{bmatrix}\Delta u_i(k)\\ \vdots\\ \Delta u_i(k+m-1)\end{bmatrix}, U_l=U_l^{c-1}$$

$$U_{-i}=\begin{bmatrix}\Delta u_i(k-1)\\ \vdots\\ \Delta u_i(k-N)\end{bmatrix}, U_{-l}=\begin{bmatrix}\Delta u_l(k-1)\\ \vdots\\ \Delta u_l(k-N)\end{bmatrix}$$

$$G_i=\begin{bmatrix} g_{i1} & 0 & & \dots & 0\\ g_{i2} & g_{i1} & & \dots & 0\\ \vdots & \vdots & & \ddots & \vdots\\ g_{ip} & g_{i(p-1)} & & \dots & g_{i(p-m+1)}\end{bmatrix}_{p*m}$$

$$G_{il}=\begin{bmatrix} g_{il1} & 0 & & \dots & 0\\ g_{il2} & g_{il1} & & \dots & 0\\ \vdots & \vdots & & \ddots & \vdots\\ g_{ilp} & g_{il(p-1)} & & \dots & g_{il(p-m+1)}\end{bmatrix}_{p*m}$$

$$H_i=\begin{bmatrix} g_{i2}-g_{i1} & \dots & g_{i(N+1)}-g_{iN}\\ \vdots & \ddots & \vdots\\ g_{i(p+1)}-g_{i1} & \dots & g_{i(N+p)}-g_{iN}\end{bmatrix}_{p*N}$$

$$H_{il}=\begin{bmatrix} g_{il2}-g_{il1} & \dots & g_{il(N+1)}-g_{ilN}\\ \vdots & \ddots & \vdots\\ g_{il(p+1)}-g_{il1} & \dots & g_{il(N+p)}-g_{ilN}\end{bmatrix}_{p*N}$$

The closed-form solution of optimal future control inputs vector of subsystem i could be analytically calculated by computing the following derivative equation:

$$\frac{\partial J_i}{U_i}=0\rightarrow {U_i}^{Opt}=\left({G_i}^T Q_i G_i+R_i\right)^{-1}{G_i}^T Q_i\left(W - \sum_{l\neq i} G_{il}U_l - Free\ Response_i\right) \tag{17}$$

It should be noted that the linear DMPC algorithms could have any limitations, for example in a distributed DMC algorithm, it must be considered that the nominal nonlinear system should not be unstable [22].

In the EDMC algorithm the $\hat{n}_i(k+j)$ consists of two parts, one part is measurable or unmeasurable external disturbances similar to DMC, and the other part is the disturbances due to the mismatch (uncertainty) between the linearized and nonlinear models which will be presented by mismatch disturbance matrix D_{nl_i}. The objective of the proposed CDEDMC algorithm is to compensate for this mismatch.

In the proposed CDEDMC algorithm the disturbance matrix is added to the free response to compensate for the mismatch between linearized and nonlinear models. So the prediction vector of subsystem i is reconstructed as:

$$Y_i = G_i U_i + \sum_{l \neq i} G_{il} U_l + Free\ Response_i + D_{nl_i} \tag{18}$$

where $Free\ Response_i$ is presented in Equ. 16 and:

$D_{nl_i} = [d_{nl_i}(k+1) \quad d_{nl_i}(k+2) \quad \cdots \quad d_{nl_i}(k+p)]^T$

where $d_{nl_i} \in R^{n_{d_{nl_i}}}$. The mismatch between linearized and nonlinear models of all subsystems should be compensated. Thus, the following equation should be solved in which the predicted outputs of the linearized and nonlinear models must be equal to each other:

$$Y_i^{linearized\ predictor} = Y_i^{nonlinear\ predictor} \tag{19}$$

The elements of D_{nl_i} will be calculated via solving the Equ. 19, and so the mismatch will be compensated. The proposed CDEDMC algorithm solves the following optimization problem for subsystem i at each iteration which has been established based on the novel cooperative optimization approach proposed in section 3. At the first step, the vector of future control inputs which was calculated using distributed DMC algorithm (Equ. 17) is defined as a function of mismatch disturbance matrix D_{nl_i}:

$$U_i(D_{nl_i}) = \left(G_i^T Q_i G_i + R_i\right)^{-1} G_i^T Q_i \left(W - \sum_{l \neq i} G_{il} \mathrm{U}_l - Free\ Response_i - D_{nl_i}\right) \tag{20}$$

$$\min_{D_{nl_i}} J(k), \qquad i = 1,2, \dots, M \tag{21}$$

Subject to Equ. 3, and Equ. 19.

$$u_i(k+j) \in U_i, j = 0, \dots, m-1 \tag{22}$$

$$U_l^c(D_{nl_i}) = U_l^{c-1}(D_{nl_i}), \forall l \in L \ and \ l \neq i \tag{23}$$

$$\left\| \hat{y}_i(k+p) - \hat{y}_{NL_i}(k+p) \right\|_{Q_i}^2 \in \frac{p}{k} y_t \tag{24}$$

with:

$$J(k) = \alpha_i J_i + \sum_l \alpha_l J_l \tag{25}$$

$$\alpha_i, \alpha_l > 0, \alpha_i + \sum_l \alpha_l = 1 \tag{26}$$

and:

$$J_i(k) = \sum_{j=1}^{p} \left[\left\| \hat{y}_i(k+j) - \hat{y}_{NL_i}(k+j) \right\|_{Q_i}^2 + \left\| d_{nl_i}(k+j) \right\|_{R_i}^2 \right] \tag{27}$$

the cost function is represented as the matrix form of:

$$J_i = \left(Y_i - Y_{NL_i}\right)^T Q_i \left(Y_i - Y_{NL_i}\right) + D_{nl_i}{}^T R_i D_{nl_i} \tag{28}$$

where Y_i is defined in Equ. 18 and Y_{NL_i} is the nonlinear prediction vector:

$Y_{NL_i} = [\hat{y}_{NL_i}(k+1) \quad \hat{y}_{NL_i}(k+2) \quad \cdots \quad \hat{y}_{NL_i}(k+p)]^T$

By solving the optimization problem in Equs. 20-27, the mismatch between linearized and nonlinear models is compensated and the optimal control input trajectory $U_i^{Opt}(D_{nl_i})$ is obtained. The optimal control input is then calculated as:

$$u_i{}^{Opt}(k) = \Delta u_i{}^{Opt}(k) + u_i{}^{Opt}(k-1) \tag{29}$$

where according to receding horizon criteria the optimal increment control input $\Delta u_i{}^{Opt}(k)$ is the first element of $U_i^{Opt}(D_{nl_i})$. The order of $U_i^{Opt}(D_{nl_i})$ is $m \times 1$ and the order of nonlinear prediction vector Y_{NL_i} is $p \times 1$ so to calculate the $u_i{}^{Opt}$ in the nonlinear prediction process in MATLAB, the control signal vector $U_{+_i}(D_{nl_i})$ is considered as follows:

$U_i(D_{nl_i}) = [U_i(D_{nl_i}) \quad 0_{(p-m)\times 1}]^T$

where the $0_{(p-m)\times 1}$ is the zero-column matrix.

In the proposed constrained CDEDMC algorithm, the mismatch between linearized and nonlinear models is compensated so if the reference trajectory moves farther away from the equilibrium point, the simulation results illustrate the desirable effect of this algorithm, while the system may be unstable using the distributed DMC algorithm. However, if the reference trajectory is farther away from the equilibrium point too much or the nonlinearity of the system is high, then the proposed CDEDMC algorithm will also lead to an unstable response. This problem will be completely solved by the following proposed constrained CDGPC method.

B. Proposed Constrained CDGPC Approach

The concept of the GPC algorithm is established based on the transfer function of the system [22]. The distinctive feature of this method is that it can be used in the non-minimum phase and unstable systems. The mismatch between linearized and nonlinear models is compensated via the online identification procedure in the proposed CDGPC approach. The denominator and numerator polynomials of the linearized model are identified using input and output information of the nonlinear large-scale system and an online RLS algorithm. The linearized model of each nonlinear subsystem is obtained using online identification in each time step and then by means of the identified numerator and denominator polynomials, free responses of nominal nonlinear subsystems, and GPC algorithm, the vector of optimal control inputs will be calculated using the proposed cooperative optimization approach in section 3. The obtained optimal control inputs are applied to the nonlinear system and this procedure iterates in the next iteration. The free responses of nonlinear subsystems are yielded from their corresponding past information.

Suppose that the linearized version of the nonlinear model of subsystem i is identified as the following transfer function:

$$y_i(k) = \frac{B_{ii}^I(z^{-1})}{A_{ii}^I(z^{-1})} u_i(k) + \sum_{l\neq i} \frac{B_{il}^I(z^{-1})}{A_{ii}^I(z^{-1})} u_l(k) \tag{30}$$

The CDGPC matrices will be calculated using the newly identified polynomials of the linearized model and finally, the optimal control input will be obtained using these new CDGPC matrices. The optimal controls will be achieved using the new CDGPC matrices which are obtained using the identified polynomials. The proposed CDGPC approach solves the following optimization problem at each iteration for subsystem i, which is established based on the proposed cooperative optimization approach in section 3:

$$\min_{\Delta u_i(k),\dots,\Delta u_i(k+m-1)} J(k) \tag{31}$$
$$U_i = [\Delta u_i(k), \dots, \Delta u_i(k+m-1)]^T$$

Subject to Equ. 30 $\forall i = 1, \dots, M$ and $l \subset L, l \neq i$.

$$u_i(k+j) \in U_i, j = 0, \dots, m-1 \tag{32}$$

$$U_l^c = U_l^{c-1}, \forall l \in L \text{ and } l \neq i \tag{33}$$

$$\|\hat{y}_i(k+p) - W(k+p)\|_{Q_i}^2 \in \frac{p}{k} y_t \tag{34}$$

with:

$$J(k) = \alpha_i J_i + \sum_l \alpha_l J_l \tag{35}$$

$$\alpha_i, \alpha_l > 0, \alpha_i + \sum_l \alpha_l = 1 \tag{36}$$

and:

$$J_i(k) = \sum_{j=1}^{p} \|\hat{y}_i(k+j) - W(k+j)\|_{Q_i}^2 + \sum_{j=1}^{m} \|\Delta u_i(k+j-1)\|_{R_i}^2 \tag{37}$$

the cost function is represented as the following matrix form:

$$J_i = (Y_i - W)^T Q_i (Y_i - W) + U_i^T R_i U_i \tag{38}$$

where the predicted output matrix is as follows:

$$Y_i = \emptyset_i^I Y_{-_i} + \pi_i^I U_{-_i} + \sum_{l\neq i} \pi_{il}^I U_{-_l} + \Omega_i^I U_i + \sum_{l\neq i} \Omega_{il}^I U_l \tag{39}$$

The closed-form solution of the vector of optimal future control of subsystem i could be analytically calculated by solving the following equation:

$$\frac{\partial J_i}{U_i} = 0 \rightarrow U_i^{Opt} = \left(\Omega_i^{I^T} Q_i \Omega_i^I + R_i\right)^{-1} G_i^T Q_i \left(W - \emptyset_i^I Y_{-_i} - \pi_i^I U_{-_i} - \sum_{l\neq i} \pi_{il}^I U_{-_l} - \sum_{l\neq i} \Omega_{il}^I U_l\right) \tag{40}$$

where:

$$Y_i = \begin{bmatrix} \hat{y}_i(k+1) \\ \vdots \\ \hat{y}_i(k+p) \end{bmatrix}_{p\times 1}, Y_{-_i} = \begin{bmatrix} y_i(k) \\ \vdots \\ y_i(k-n_{a_i}^I) \end{bmatrix}_{(n_{a_i}^I+1)\times 1}$$

$$U_i = \begin{bmatrix} \Delta u_i(k) \\ \vdots \\ \Delta u_i(k+m-1) \end{bmatrix}_{m\times 1}, \quad U_l = U_l^{c-1}$$

$$U_{-_i} = \begin{bmatrix} \Delta u_i(k-1) \\ \vdots \\ \Delta u_i(k-n_{b_i}^I) \end{bmatrix}_{n_b^I\times 1}, U_{-_l} = \begin{bmatrix} \Delta u_l(k-1) \\ \vdots \\ \Delta u_l(k-n_{b_{il}}^I) \end{bmatrix}$$

in which $n_{a_i}^I$, $n_{b_i}^I$ and $n_{b_{il}}^I$ are the orders of the A_{ii}^I, B_{ii}^I and B_{il}^I identified polynomials respectively.

The $\hat{y}_i(k+j), (j = 1,2, \dots p)$, is calculated using extended CARIMA and Diophantine equations via the following process and supposing that the time delay is zero:

$$\Delta A_{ii}^I(z^{-1}) y_i(k) = \left[B_{ii}^I(z^{-1})\Delta u_i(k-1) + \sum_{l\neq i} B_{il}^I(z^{-1})\Delta u_l(k-1)\right] + C_i^I(z^{-1}) e_i(k) \tag{41}$$

$$1 = E_{i\ j}^I(z^{-1}) \Delta A_{ii}^I(z^{-1}) + z^{-j} F_{i\ j}^I(z^{-1}) \tag{42}$$

where:

$$F_{i\ j}^I(z^{-1}) = f_{i_{(j,0)}} + f_{i_{(j,1)}} z^{-1} + \dots + f_{i_{(j,n_{a_i}^I)}} z^{-n_{a_i}^I} \tag{43}$$

$$E_{i\ j}^I(z^{-1}) = e_{i_{(j,0)}} + e_{i_{(j,1)}} z^{-1} + \dots + e_{i_{(j,j-1)}} z^{-(j-1)} \tag{44}$$

in which the coefficients of $F_{i\ j}^I(z^{-1})$ and $E_{i\ j}^I(z^{-1})$ are computed using the recursive procedure as follows:

$$F_{i\ 1}^I = z(1 - \Delta A_{ii}^I(z^{-1})) \tag{45}$$

$$E_{i\ 1}^I = 1 \tag{46}$$

$$E_{i\ j+1}^I(z^{-1}) = E_{i\ j}^I(z^{-1}) + f_{i_{(j,0)}} z^{-j} \tag{47}$$

$$f_{i_{(j+1,q)}} = f_{i_{(j,q+1)}} - f_{i_{(j,0)}} - f_{j,0} \tilde{a}_{i_{(q+1)}} \tag{48}$$

where $\tilde{a}_{i_{(q+1)}}$ $(q = 0, 1, \dots, n_{a_i}^I)$ are the coefficients of the $\Delta A_{ii}^I(z^{-1})$ polynomial. The future outputs are achieved using Equs. 41-42:

$$y_i(k+j) = F^I_{i\,j}(z^{-1})y_i(k) + E^I_{i\,j}(z^{-1})\left[B^I_{ii}(z^{-1})\Delta u_i(k+j-1) + \sum_{l\neq i} B^I_{il}(z^{-1})\Delta u_l(k+j-1)\right] + E^I_{i\,j}(z^{-1})e_i(k+j) \quad (49)$$

The appropriate estimation of prediction of $y_i(k+j)$ is its average so we have:

$$\hat{y}_i(k+j) = G^I_{i\,j}(z^{-1})\Delta u_i(k+j-1) + \sum_{l\neq i} G^I_{il_j}(z^{-1})\Delta u_l(k+j-1) + F^I_{i\,j}(z^{-1})y_i(k), \qquad j=1,\dots,p \quad (50)$$

$$G^I_{i\,j}(z^{-1}) = B^I_{ii}(z^{-1})E^I_{i\,j}(z^{-1}) \quad (51)$$

$$G^I_{il_j}(z^{-1}) = B^I_{il}(z^{-1})E^I_{i\,j}(z^{-1}) \quad (52)$$

Since the $e_i(k+j)$ is the white Gaussian noise thus, its average is zero. The new CDGPC matrices in Equ. 39 are expressed as:

$$\emptyset^I_i = \begin{bmatrix} f_{i(1,0)} & \cdots & f_{i(1,n^I_{a_i})} \\ \vdots & \ddots & \vdots \\ f_{i(p,0)} & \cdots & f_{i(p,n^I_{a_i})} \end{bmatrix}$$

$$\pi^I_i = \begin{bmatrix} g_{i(1,1)} & g_{i(1,2)} & \cdots & g_{i(1,n^I_{b_i})} \\ \vdots & \vdots & \ddots & \vdots \\ g_{i(p,p)} & g_{i(p,p+1)} & \cdots & g_{i(p,n^I_{b_i})} \end{bmatrix}$$

$$\pi^I_{il} = \begin{bmatrix} g_{il(1,1)} & g_{il(1,2)} & \cdots & g_{il(1,n^I_{b_{il}})} \\ \vdots & \vdots & \ddots & \vdots \\ g_{il(p,p)} & g_{il(p,p+1)} & \cdots & g_{il(p,n^I_{b_{il}})} \end{bmatrix}$$

$$\Omega^I_i = \begin{bmatrix} g_{i(1,0)} & 0 & 0 & \cdots & 0 \\ g_{i(2,1)} & g_{i(2,0)} & 0 & & 0 \\ & \vdots & & \ddots & \vdots \\ g_{i(p,p-1)} & g_{i(p,p-2)} & \cdots & \cdots & g_{i(p,0)} \end{bmatrix}$$

$$\Omega^I_{il} = \begin{bmatrix} g_{il(1,0)} & 0 & 0 & \cdots & 0 \\ g_{il(2,1)} & g_{il(2,0)} & 0 & & 0 \\ & \vdots & & \ddots & \vdots \\ g_{il(p,p-1)} & g_{il(p,p-2)} & \cdots & \cdots & g_{il(p,0)} \end{bmatrix}$$

where $g_{i(j,q)}$ and $g_{il(j,q)}$ $(j=1,2,\dots,p, q=1,2,\dots)$ are the corresponding coefficients of the $G^I_{i\,j}(z^{-1})$ and $G^I_{i\,j}(z^{-1})$ polynomials respectively.

V. Simulation Results

A typical nonlinear large-scale system consisting of three coupled subsystems is employed as following input-output models to investigate the proposed approaches:

$$\begin{cases} \dot{y}_1(t) = -y_1(t) + y_1(t)^2 + 7u_1(t) + 4u_2(t) \\ \dot{y}_2(t) = -3y_2(t) + 2y_2(t)^2 + 10u_2(t) + u_3(t)^2 \\ \dot{y}_3(t) = -2y_3(t) + y_3(t)^2 + 2u_3(t) + u_2(t) \end{cases}$$

The subsystems are coupled through inputs. The discrete-time system could be obtained using the following Euler derivative approximation:

$$\dot{y}_i(t) = \left(y_i(k+1) - y_i(k)\right)/T_s$$

so the discrete-time system is concluded as:

$$\begin{cases} y_1(k+1) = a_1y_1(k) + 0.1y_1(k)^2 + 0.7u_1(k) + 0.4u_2(k) \\ y_2(k+1) = a_2y_2(k) + 0.2y_2(k)^2 + u_2(k) + 0.1u_3(k)^2 \\ y_3(k+1) = a_3y_3(k) + 0.1y_3(k)^2 + 0.2u_3(k) + 0.1u_2(k) \end{cases}$$

where the sampling time is $T_s = 0.1$ and:

$a_1 = 0.9, a_2 = 0.7, a_3 = 0.8$

The step responses of subsystems are drawn in Fig. 1. According to the step responses the subsystems' settling times are approximately 6, 2, and 3 respectively. So the subsystems' optimal model horizons are:

$N = (Settling\ Time)/T_s \rightarrow N_1 = 60, N_2 = 20, N_3 = 30$

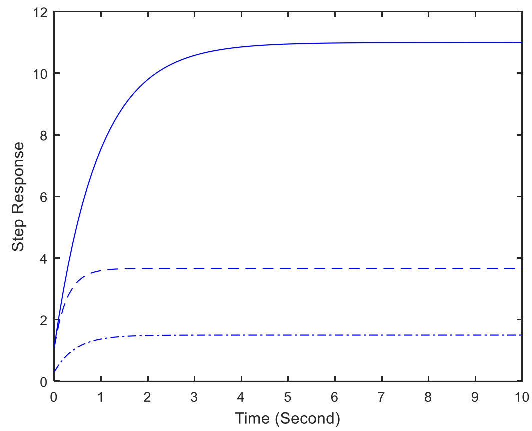

Fig. 1. Step responses, subsystem 1 (solid line), subsystem 2 (dash line), subsystem 3 (dash dot line).

Note that in all simulations the subsystems' model horizons are considered $N_1 = 60, N_2 = 20$ and $N_3 = 30$ respectively and also the subsystems' prediction and control horizons are considered 5 and 4 respectively.

The following constraint is imposed to control inputs:

$-4 \le u_i \le 4, i = 1,2,3$

The reference trajectory is considered as the following equation:

$$W(t) = g_W * \begin{cases} 0.01 & 0 \le t < 2.5 \\ 0.02 & 2.5 \le t < 5 \\ -0.01 & 5 \le t < 7.5 \\ 0 & 7.5 \le t < 10 \end{cases}$$

where the g_W is the amplitude's coefficient of the reference trajectory. In the first step of the simulation, we set the amplitude's coefficient as $g_W = 10$ to consider the reference trajectory a little farther away from the origin (equilibrium point). Therefore, the subsystems' predicted outputs are illustrated in Figs. 2-4 using distributed DMC and proposed constrained CDEDMC and CDGPC algorithms respectively.

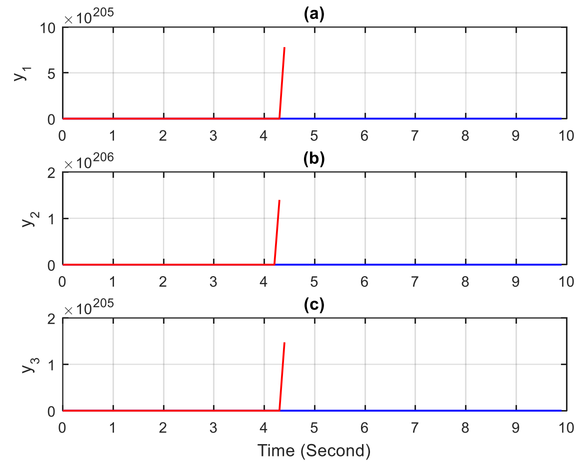

Fig. 2. The predicted outputs of the nonlinear large-scale system with $g_W = 10$ and using cooperative distributed DMC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

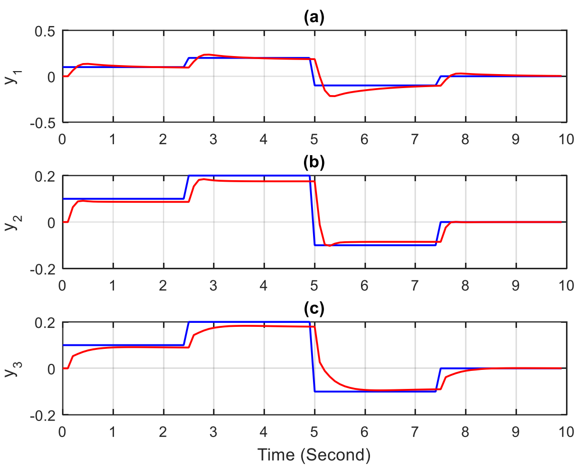

Fig. 3. The predicted outputs of the nonlinear large-scale system with $g_W = 10$ and using proposed constrained CDEDMC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

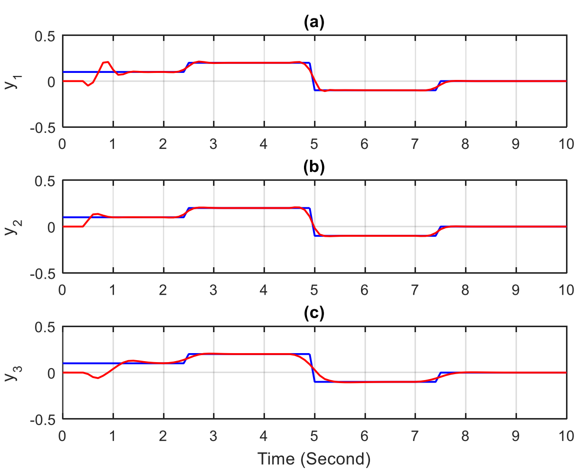

Fig. 4. The predicted outputs of the nonlinear large-scale system with $g_W = 10$ and using proposed constrained CDGPC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

Since in both CDEDMC and CDGPC algorithms the mismatch between linearized and nonlinear models is compensated, it is expected to obtain appropriate responses. The illustrated predicted output curves in Figs. 3-4 confirm this from design criteria points of view such as convergence, reference trajectory's tracking and stability. However, even though the reference trajectory is not too far from the origin, according to Fig. 2, the system has become unstable using the distributed DMC algorithm.

To further emphasize the effectiveness of proposed constrained CDEDMC and CDGPC algorithms and compare them to each other, the reference trajectory's amplitude is gradually increased; $g_W = 50, 80, 110$, and simulation results are shown in Figs. 5-10.

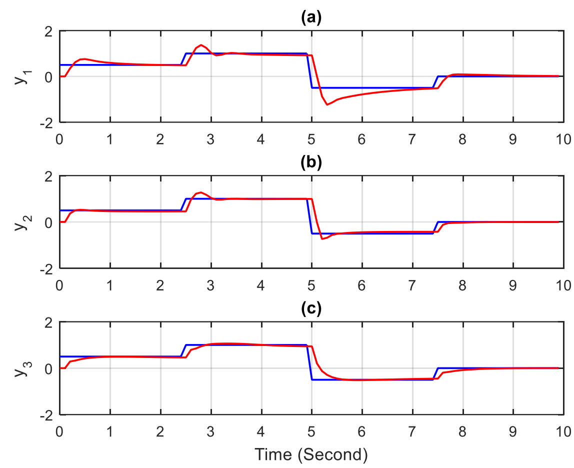

Fig. 5. The predicted outputs of the nonlinear large-scale system with $g_W = 50$ and using proposed constrained CDEDMC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

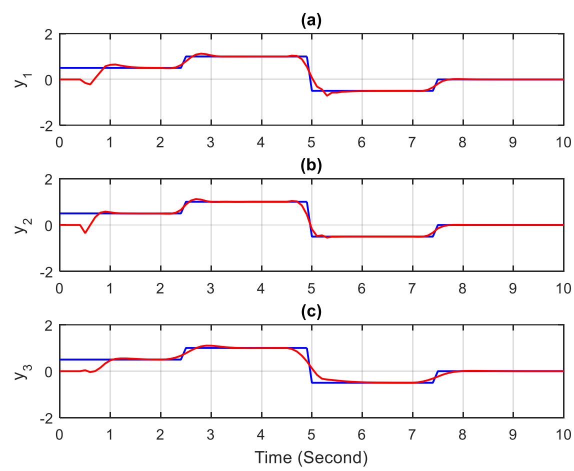

Fig. 6. The predicted outputs of the nonlinear large-scale system with $g_W = 50$ and using proposed constrained CDGPC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

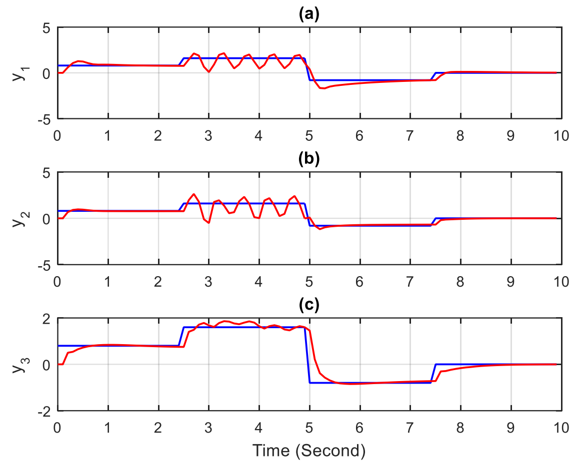

Fig. 7. The predicted outputs of the nonlinear large-scale system with $g_W = 80$ and using proposed constrained CDEDMC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

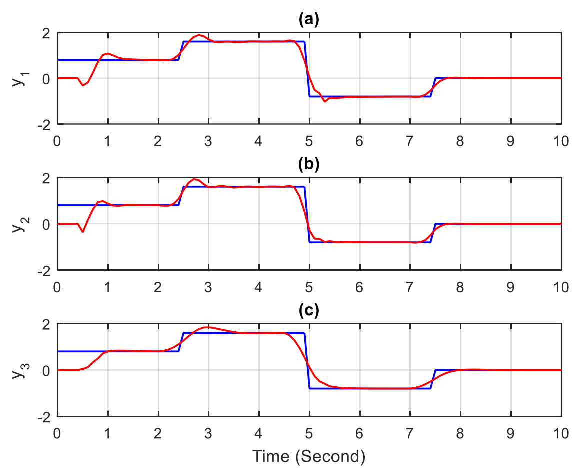

Fig. 8. The predicted outputs of the nonlinear large-scale system with $g_W = 80$ and using proposed constrained CDGPC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

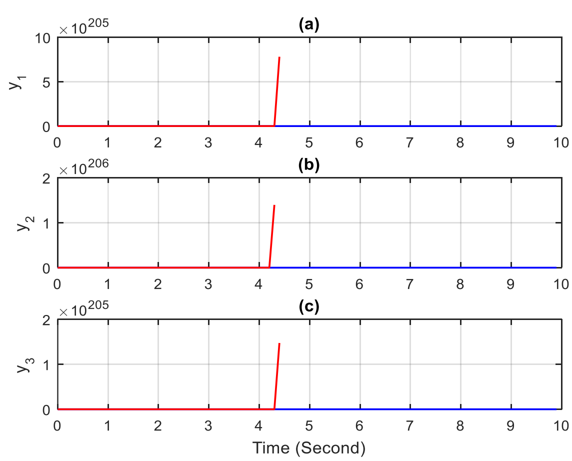

Fig. 9. The predicted outputs of the nonlinear large-scale system with $g_W = 110$ and using proposed constrained CDEDMC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

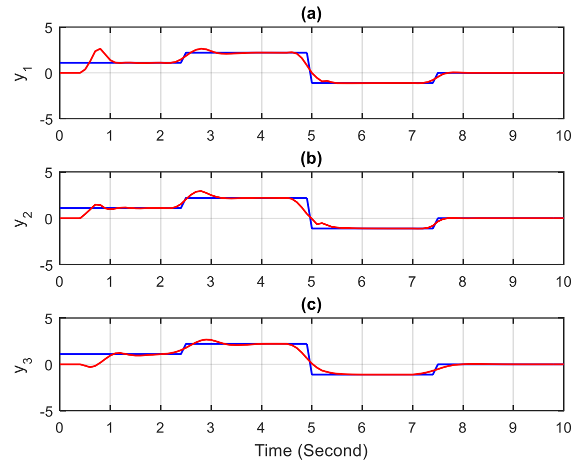

Fig. 10. The predicted outputs of the nonlinear large-scale system with $g_W = 110$ and using proposed constrained CDGPC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

when the amplitude's coefficient is $g_W = 50$, both methods have proper responses according to results in Figs. 5-6, however, according to Fig. 7 by increasing the g_W to 80 some fluctuations appear when the CDEDMC is applied, while based on illustrated results in Fig. 8, the CDGPC shows appropriate predictions. The initial overshoots or undershoots in CDGPC's results are due to its online identification of the mismatch between linearized and nominal nonlinear models, and after a short time that the identification of the linearized system's numerator and denominator polynomials is done, the response becomes convergent. The usefulness of the proposed constrained CDGPC algorithm is more demonstrated when the reference trajectory is too farther away from the origin, hence to investigate this issue the amplitude's coefficient of the reference is increased to $g_W = 110$ and the simulation results are drawn in Figs. 9-10 using proposed constrained CDEDMC and CDGPC algorithms respectively. According to Fig. 9, the system has become unstable using the DEDMC algorithm, while based on illustrated results in Fig. 10, the CDGPC shows appropriate predictions and the closed-loop system is stable.

Now the proposed approaches are examined when uncertainty is applied. Assuming that in the fourth second of simulation, a_1, a_2 and a_3 change as:

$a_1^{new} = a_2^{new} = a_1^{new} = 0.4$

The simulation results are depicted in Figs. 11-12 with $g_W = 50$. The results emphasize the effectiveness of proposed algorithms in dealing with uncertainty. Although the responses fluctuate when the uncertainties are imposed, they quickly converge.

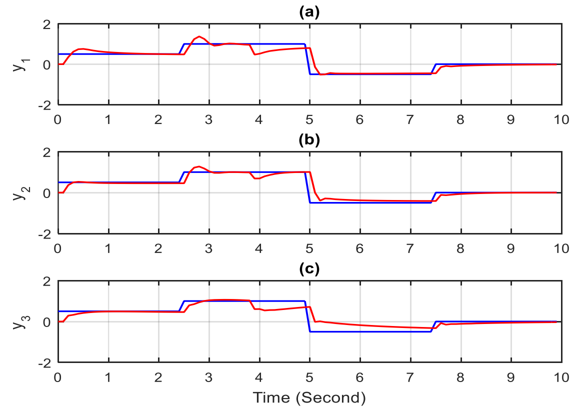

Fig. 11. The predicted outputs of the nonlinear large-scale system with imposed uncertainties and $g_W = 50$ and using proposed constrained CDEDMC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

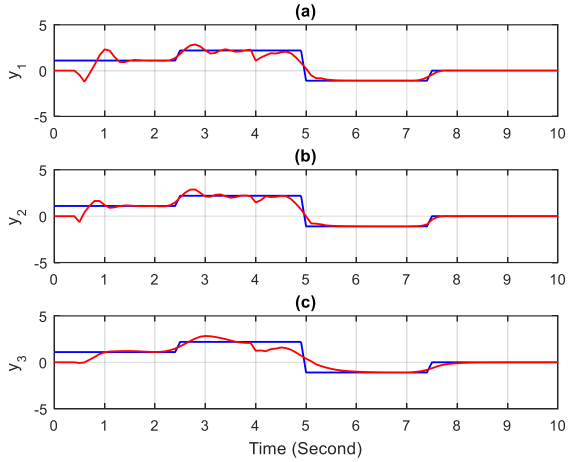

Fig. 12. The predicted outputs of the nonlinear large-scale system with imposed uncertainties and $g_W = 50$ and using proposed constrained CDGPC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

All the above-mentioned results are yielded using the novel cooperative optimization approach proposed in section 3 where each subsystem optimizes a corresponding global cost function which is a convex combination of its cost function and cost functions of its neighbors. For example in the large-scale system which is analyzed in this section, subsystem 1 is neighbor to subsystem 2, but not to subsystem 3. Therefore, according to the proposed optimization approach, the global cost function, which is optimized in the local controller of subsystem 1 is represented as follows:

$$J = \alpha_1 J_1 + \alpha_2 J_2, \qquad \alpha_1 + \alpha_2 = 1$$

while according to typical cooperative DMPC methods, the global cost function is defined based on all three subsystems [1, 21]:

$$J = J_1 + J_2 + J_3$$

So the control efforts, cost function values, and convergence time are reduced using the proposed cooperative optimization approach. These criteria are examined by means of the following simulation results in which the proposed optimization approach and the DGPC algorithm are used. The cost function values of the local controllers of the nonlinear large-scale system with the mentioned imposed uncertainties are illustrated in Figs. 13-15 respectively with $g_W = 50$ and applying typical [1, 21] and proposed cooperative optimization strategies. It is cleared that the cost function values have decreased in the proposed cooperative optimization approach compared to the typical one.

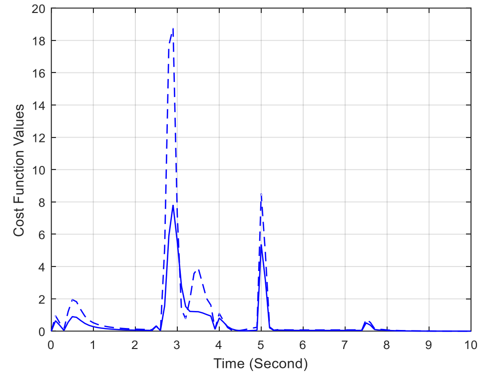

Fig. 13. The cost function values of the local controller of the uncertain subsystem 1 with $g_W = 50$ and using typical (dash line) and proposed (solid line) cooperative optimization strategies.

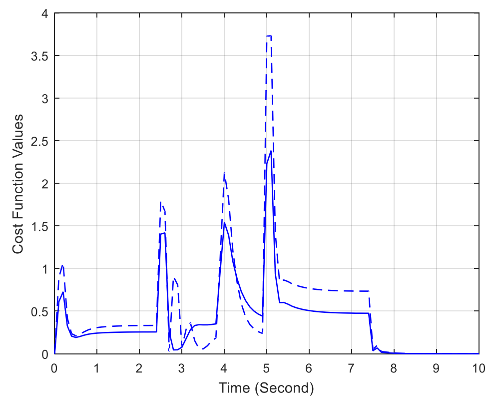

Fig. 14. The cost function values of the local controller of the uncertain subsystem 2 with $g_W = 50$ and using typical (dash line) and proposed (solid line) cooperative optimization strategies.

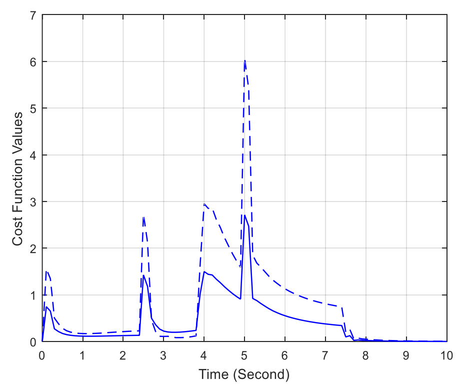

Fig. 15. The cost function values of the local controller of the uncertain subsystem 3 with $g_W = 50$ and using typical (dash line) and proposed (solid line) cooperative optimization strategies.

To further investigate and clarify the performance and effectiveness of the proposed cooperative optimization approach, besides the comparison of the cost function values in Figs. 13-15, additional indicators including maximum, average, and standard deviation of cost function values are also calculated and collected in the following tables [23, 24].

TABLE I
Maximum, Average And Standard Deviation Indicators Of Cost Function Values Of Subsystem 1

Subsystem 1	Max	Avg	Std
Proposed cooperative optimization strategy	12.3619	0.8072	2.0687
Typical cooperative optimization strategy	18.7688	0.9912	2.8268

TABLE II
Maximum, Average And Standard Deviation Indicators Of Cost Function Values Of Subsystem 2

Subsystem 2	Max	Avg	Std
Proposed cooperative optimization strategy	2.4535	0.3947	0.45
Typical cooperative optimization strategy	3.7308	0.5011	0.64

TABLE III
Maximum, Average And Standard Deviation Indicators Of Cost Function Values Of Subsystem 3

Subsystem 3	Max	Avg	Std
Proposed cooperative optimization strategy	2.6338	0.3152	0.4367
Typical cooperative optimization strategy	6.0683	0.7612	1.0638

According to the values of indicators in Table 1-3, it is clear that all three maximum, average, and standard deviation of cost function values are decreased in the proposed cooperative optimization approach compared to the typical one.

Fig. 16, illustrates the predicted outputs of the nonlinear large-scale system without uncertainty, which are obtained using a typical cooperative optimization approach in [1, 21] and DGPC algorithm with $g_W = 50$, and also Fig. 6, illustrates the predicted outputs of the nonlinear large-scale system without uncertainty using the proposed cooperative optimization approach in this paper and DGPC algorithm with $g_W = 50$. By comparing the results in Fig. 6 and Fig. 16, it is concluded that the time and quality of convergence have improved in the proposed constrained CDGPC (Fig. 6) compared to the typical one in [1, 21] (Fig. 16).

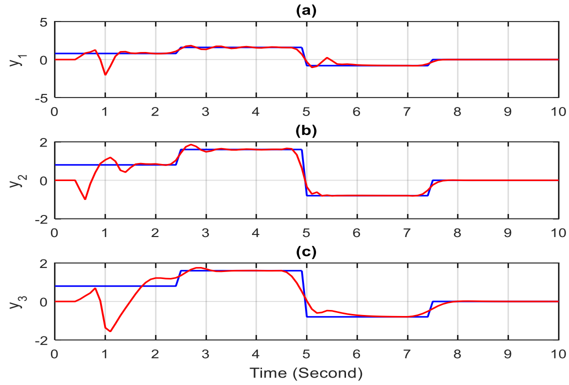

Fig. 16. The predicted outputs of the nonlinear large-scale system with $g_W = 50$ and using typical CDGPC algorithm. (a) Subsystem 1; (b) subsystem 2; (c) subsystem 3.

VI. CONCLUSION

In this manuscript, a novel cooperative DMPC approach is proposed which improves the global cost function. Each local controller optimizes the global cost function which is a convex combination of its own and its neighbors' cost functions instead of the combination of its own and all other subsystems' cost functions. So the computational burden of optimization, cost values, and convergence time are reduced compared to typical cooperative DMPC methods. Two linear cooperative constrained distributed model predictive controllers; CDEDMC and CDGPC are proposed which employ the proposed cooperative optimization approach to control the uncertain nonlinear large-scale systems. The simulation results of an uncertain nonlinear large-scale system consisting of three interconnected subsystems demonstrate the effectiveness of the proposed approaches. According to simulation results, typical distributed linear algorithms like DMC lead to an unstable closed-loop response if the reference trajectory is far from the equilibrium point, while this problem is solved using proposed CDEDMC and CDGPC algorithms even if the reference trajectory is too far from the equilibrium point.

REFERENCES

[1] P. D. Christofides, R. Scattolini, D. M. De la Pena, and J. Liu, "Distributed model predictive control: A tutorial review and future research directions" *Journal of Computers and Chemical Engineering*, Vol. 51, pp. 21-41, Apr. 2013.

[2] A. Grancharova, T. A. Johansen, and S. Olaru, "Dual-Mode distributed model predictive control of a quadruple-tank system" *Journal of Chemical Technology and Metallurgy*, Vol. 53, No. 4, pp. 674-682, May. 2018.

[3] N. Sadati, M. Rahmani, and M. Saif, "Two-Level Robust Optimal Control of Large-Scale Nonlinear Systems" *IEEE Systems Journal*, Vol. 9, No. 1, pp. 242-251, Mar. 2015.

[4] I. Stoyanova, E. Gumrukcu, G. Aragon, D. I.

Hidalgo-Rodriguez, A. Monti, and J. Myrzik, "Distributed model predictive control strategies for coordination of electro-thermal devices in a cooperative energy management concept" *Optimal Control Applications and Methods*, Vol. 41, pp. 170–189, Aug. 2019.

[5] Y. Zou, X. Su, S. Li, Y. Niu, and D. Li, "Event-triggered distributed predictive control for asynchronous coordination of multi-agent systems" *Automatica*, Vol. 99, pp. 92–98, Jan. 2019.

[6] W. Jiao, Q. Wu, S. Huang, and J. Chen, "Decentralized voltage control of wind farm based on gradient projection method" *International Journal of Electrical Power & Energy Systems*, Vol. 123, pp. 1-8, Dec. 2020.

[7] Y. Gao, L. Dai, Y. Xia, and Y. Liu, "Distributed model predictive control for consensus of nonlinear second-order multi-agent systems" *International Journal of Robust and Nonlinear Control*, Vol. 27, pp. 830-842, Jul. 2016.

[8] X. Liu, Y. Shi, and D. Constantinescu, "Distributed model predictive control of constrained weakly coupled nonlinear systems" *Systems & Control Letters*, Vol. 74, pp. 41-49, Dec. 2014.

[9] S. Rahmati, and H. Eliasi, "Robust Decentralized Model Predictive Control for a Class of Interconnected systems" *International Journal of Industrial Electronics, Control and Optimization*, Vol. 3, No. 3, pp. 327-336, Jul. 2020.

[10] M. H. Yamchi, and R. M. Esfanjani, "Distributed predictive formation control of networked mobile robots subject to communication delay" *Robotics and Autonomous Systems*, Vol. 91, pp. 194-207, May. 2017.

[11] X. Liu, Y. Shi, and D. Constantinescu, "Robust Distributed Model Predictive Control of Constrained Continuous-Time Nonlinear Systems Using Two-Layer Invariant Sets" *Journal of Dynamic Systems, Measurement, and Control*, Vol. 138, pp.1-7, Jun. 2016.

[12] Y. Zheng, S. Eben Li, K. Li, F. Borrelli, and J. Karl Hedrick, "Distributed Model Predictive Control for Heterogeneous Vehicle Platoons under Unidirectional Topologies" *IEEE Transactions on Control Systems Technology*, Vol. 25, No. 3, pp. 899-910, May. 2017.

[13] X. Yang, L. Zhang, W. Xie, and J. Zhang, "Sequential and Iterative Distributed Model Predictive Control of Multi-Motor Driving Cutterhead System for TBM" *IEEE Access*, Vol. 7, pp. 46977-46989, Apr. 2019.

[14] S. Iles, J. Matusko, and F. Kolonic, "Sequential distributed predictive control of a 3D tower crane" *Control Engineering Practice*, Vol. 79, pp. 22-35, Oct. 2018.

[15] Y. Long, S. Liu, L. Xie, and K. H. Johansson, "Distributed nonlinear model predictive control based on contraction theory" *International Journal of Robust and Nonlinear Control*, Vol. 28, pp. 1–12, Jul. 2017.

[16] X. Liu, Y. Shi, and D. Constantinescu, "Robust distributed model predictive control of constrained dynamically decoupled nonlinear systems: A contraction theory perspective" *Systems & Control Letters*, Vol. 105, pp. 84-91, Jul. 2017.

[17] N. R. Esfahani and K. Khorasani, "A Distributed Model Predictive Control (MPC) Fault Reconfiguration Strategy for Formation Flying Satellites" *International Journal of Control*, Vol. 89, No. 5, pp. 960-983, Nov. 2015.

[18] X. Kong, X. Liu, L. Ma, and K. Y. Lee, "Hierarchical Distributed Model Predictive Control of Standalone Wind/Solar/Battery Power System" *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 49, No. 8, pp. 1570-1581, Aug. 2019.

[19] A. Mirzaei, and A. Ramezani, "Cooperative Distributed Constrained Adaptive Generalized Predictive Control for Uncertain Nonlinear Large-Scale Systems: Application to Quadruple-Tank System" *Journal of Electrical and Computer Engineering Innovations*, Vol. 7, No. 2, pp. 183-194, Jul. 2020.

[20] M. Ehsani, M. Saeidi, H. Radmanesh, and A. Abrishamifar, "Comparisons between Generalized Predictive Control and Linear Controllers in Multi-Input DC-DC Boost Converter" *International Journal of Industrial Electronics, Control and Optimization*, Vol. 1, No. 3, pp. 27-34, Jan. 2020.

[21] X. Xing, L. Xie, and H. Meng, "Cooperative energy management optimization based on distributed MPC in grid-connected microgrids community" *Electrical Power and Energy Systems*, Vol. 107, pp. 186–199, May. 2019.

[22] E. F. Camacho, and C. Bordons, "Model Predictive Control", Springer, Second Edition, Jul. 2007.

[23] E. Zakeri, S. A. Moezi, and M. Eghtesad, "Optimal interval type-2 fuzzy fractional order super twisting algorithm: A second order sliding mode controller for fully-actuated and under-actuated nonlinear systems" *ISA Transactions*, Vol. 85, pp. 13-32, Feb. 2019.

[24] E. Zakeri, and H. Moeinkhah, "Digital control design for an IPMC actuator using adaptive optimal proportional integral plus method: Simulation and experimental study" *Sensors and Actuators A: Physical*, Vol. 298, pp. 1-14, Oct. 2019.

Ahmad Mirzaei was born in Tehran, Iran, in 1983. He received the B.E. degree in Electronics Engineering majoring in Control from University of Tabriz, Tabriz, Iran, in 2007, and his M.S. in Control Engineering from Tarbiat Modares University, Tehran, Iran, in 2013. Currently he is a Ph.D. candidate in Tarbiat Modares University, Tehran, Iran. He is also a research assistant at Advanced Control Systems Laboratory in Tarbiat Modares University. His research interests include Distributed Model Predictive Control, Large-Scale Systems, Cooperative Optimization, and Robust Control.

Amin Ramezani was born in Khuzestan, Iran, in 1979. He received his B.E. degree in Electronics Engineering from Shahid Beheshti University of Tehran, Tehran, Iran, in 2001, and his M.S. degree in Control systems from Sharif University of Technology, Tehran, Iran, in 2004. He received his Ph.D. degree in Electronics Engineering from the University of Tehran, Tehran, Iran, in 2011. In 2012, he joined the Department of Electrical Engineering, Tarbiat Modares University, Tehran, Iran, as a Lecturer. He is the chair of Advanced Control Laboratory and cooperates as the PC members of some conferences and special editor and reviewer of international journals in the field of control systems. His current research interests include Fault Tolerant Control Systems, Model-Based Predictive Control Systems, Stochastic Control Systems, and Hybrid Systems. He is a member of IEEE since 2005 and a member of Iranian Community Instrument and Control Engineers since 2012.