

Automatic Generation Control of Multi-area Power System with Network Constraints and Communication Delays

Ragini Patel, Lasantha Meegahapola, Liuping Wang, Xinghuo Yu, and Brendan McGrath

Abstract—Newly proposed power system control methodologies combine economic dispatch (ED) and automatic generation control (AGC) to achieve the steady-state cost-optimal solution under stochastic operation conditions. However, a real power system is subjected to continuous demand disturbance and system constraints due to the input saturation, communication delays and unmeasurable feed-forward load disturbances. Therefore, optimizing the dynamic response under practical conditions is equally important. This paper proposes a state constrained distributed model predictive control (SCDMPC) scheme for the optimal frequency regulation of an interconnected power system under actual operation conditions, which exist due to the governor saturation, generation rate constraints (GRCs), communication delays, and unmeasured feed-forward load disturbances. In addition, it proposes an algorithm to handle the solution infeasibility within the SCDMPC scheme, when the input and state constraints are conflicting. The proposed SCDMPC scheme is then tested with numerical studies on a three-area interconnected network. The results show that the proposed scheme gives better control and cost performance for both steady state and dynamic state in comparison to the traditional distributed model predictive control (MPC) schemes.

Index Terms—Automatic generation control, constraints, distributed control, frequency regulation, model predictive control (MPC), tie-lines.

I. INTRODUCTION

THE increasing deregulation [1], [2] and penetration of the renewable energy sources (RESs) into the electricity grid leads to the stochastic operation conditions with non-zero mean demand disturbances [3]–[5], which potentially compromise the economic and control performance of the economic dispatch (ED) and automatic generation control (AGC) [6]. The new methods to optimize the operation cost under stochastic conditions are proposed in [7]–[9]. However, these methods do not explicitly consider the governor saturation and generation rate constraints (GRCs) within the

control formulation and only optimize the steady-state solution of the controller. This has motivated some researchers to explore the dynamic model predictive control (MPC) methodology for AGC as this technique enables an optimization criteria and the broad range of constraints to be incorporated into the control response [10]. Nevertheless, the MPC-based AGC schemes proposed so far have only focussed on control performance and are not designed to achieve the best cost performance at system level. In this paper, therefore, the control and economic objectives are combined in a new distributed MPC (DMPC) formulation with state constraints, which achieves ED along with AGC under real-time operation conditions.

The existing MPC-based approaches for power system AGC vary among their implementations and control strategies. For example, the traditional MPC schemes in the centralized as well as distributed implementations for AGC regulate an area control error (ACE) [11], which controls both the tie-line flow and frequency state deviation to be 0 [5]. The centralized implementations in [12] and [13] use MPC in a supervisory mode and suggest optimal set points to the local proportional-integral (PI) controllers. The benefit of a supervisory scheme is a continuous control in times of communication failure as local PI controllers can continue to control ACE. Centralized MPC in [14] replaces the traditional PI control and is applicable only to a small size system due to the high computation needs. To tackle the drawback of high communication and computational requirements of centralized MPC implementations for a large-size power system, DMPC formulations are suggested [15]–[18]. A comprehensive summary of various distributed implementations of MPC for AGC can be found in [5]. A new hierarchical MPC scheme for smart grid is proposed in [19] to include the new type of resources in the control services, but it does not consider the contribution from the conventional turbine-governor for frequency control. However, governors play a major role in the frequency regulation through AGC in current systems, so it is necessary to pay attention to their response. Nevertheless, all the MPC strategies discussed above improve the dynamic response and local area control cost as the control variable is the ACE. In an ACE-based MPC scheme, the controller converges to a local optima where a traditional PI-based AGC will also converge. Thus, a better set point at the steady state from the point of view of the

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R. Patel (corresponding author), L. Meegahapola, L. Wang, X. Yu, and B. McGrath are with Royal Melbourne Institute of Technology University, Melbourne, Vic 3000, Australia (e-mail: patel.ragini@gmail.com; lasantha.meegahapola@rmit.edu.au; liuping.wang@rmit.edu.au; x.yu@rmit.edu.au; brendan.mcgrath@rmit.edu.au).

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ED is not obtained. In addition, due to the ACE approach, the tie-line flow values stay at their scheduled values and a biased control is possible in times of large disturbances. Furthermore, the ability of self-smoothing wind fluctuations is lost [20]. A cost-optimal AGC scheme will be one which can combine the objective of ED and AGC which requires the ability to allow the tie-line flow to vary during the AGC cycle. A state constrained DMPC (SCDMPC) scheme is introduced in [21] to constrain the tie-line flow states while regulating frequency state unlike traditional AGC scheme and achieve an ED at system level. However, the control law derived in SCDMPC assumes that the communication between the distributed controllers and wide area control (WAC) is instantaneous and demand disturbances are too small to cause the input saturation. From a practical point of view, since the distributed controllers solve simultaneously, instantaneous communication is not possible. Further, in a deregulated market with more flexible communication networks [22], a communication delay is much more possible. Such circumstance means that the information of neighboring states cannot be obtained without a time lag. This also means that the load disturbances cannot be calculated by the method proposed in [21]. When the demand disturbance is large, the input constraints on governor saturation and GRCs become active. And due to the presence of constraints on tie-line states, SCDMPC optimizer can encounter infeasibility. This paper, therefore, addresses the above limitations to achieve a practical implementation of SCDMPC in a WAC framework.

The contributions of the paper are as follows: ① a shifted prediction methodology is proposed for handling communication delays between WAC and local controllers so that the full system state predictions can be made under real-time conditions; ② a functional observer is designed to estimate the feed-forward demand disturbance in presence of communication delay, which is required to correct state estimation in local controllers; ③ since the SCDMPC optimization problem has input as well as state constraints, conflicting constraint scenario can occur in times of large disturbance. An infeasibility solving algorithm is designed in such a way that the computational burden does not increase and a solution can be obtained in the current sampling time.

It has been shown in the numerical studies that the new SCDMPC methodology reduces the regulating reserve requirement for balancing services while maintaining all the operation constraints.

II. A REVIEW OF SCDMPC FOR AGC

The SCDMPC scheme proposed in [21] uses a decomposed state space model for the distributed controllers where each decomposed model is a full system state model. The full system state decomposed model is derived from the centralized state space model of the interconnected power system, given by:

$$\dot{X} = A_c X + B_c U + B_c^d d \quad (1)$$

where A_c is the state matrix for centralized system; B_c is the input matrix for centralized system; and B_c^d is the distur-

bance matrix for centralized system. To build the mathematical model, a generic directed ring interconnection is used and the state X is defined as:

$$X = \left[\underbrace{\Delta f_1 \ \Delta P_1 \ \Delta P_{g1}}_{\text{Area 1 states}} \ \underbrace{\Delta P_{12}}_{\text{Areas 1 and 2 coupling}} \ \dots \ \underbrace{\Delta f_n \ \Delta P_n \ \Delta P_{gn}}_{\text{Area } n \text{ states}} \ \underbrace{\Delta P_{n1}}_{\text{Areas } n \text{ and 1 coupling}} \right]^T \quad (2)$$

The input U is a vector of control signals to the governors in n control areas given by:

$$U = [u_1 \ u_2 \ \dots \ u_n]^T \quad (3)$$

The vector d represents unmeasured feed-forward load disturbances and $d = [\Delta P_1^L, \Delta P_2^L, \dots, \Delta P_n^L]^T$, where ΔP_n^L is the unmeasured feed-forward disturbance in n^{th} control area.

The aggregate matrices A_c , B_c and B_c^d are given below:

$$A_c = \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1n} \\ A_{21} & A_{22} & \dots & A_{2n} \\ \vdots & \vdots & & \vdots \\ A_{n1} & A_{n2} & \dots & A_{nn} \end{bmatrix} \quad (4)$$

$$B_c = \begin{bmatrix} B_{11} & 0_{4 \times 1} & \dots & 0_{4 \times 1} \\ 0_{4 \times 1} & B_{22} & \dots & 0_{4 \times 1} \\ \vdots & \vdots & & \vdots \\ 0_{4 \times 1} & 0_{4 \times 1} & \dots & B_{nn} \end{bmatrix} \quad (5)$$

$$B_c^d = \begin{bmatrix} B_{11}^d & 0_{4 \times 1} & \dots & 0_{4 \times 1} \\ 0_{4 \times 1} & B_{22}^d & \dots & 0_{4 \times 1} \\ \vdots & \vdots & & \vdots \\ 0_{4 \times 1} & 0_{4 \times 1} & \dots & B_{nn}^d \end{bmatrix} \quad (6)$$

$$A_{ii} = \begin{bmatrix} \frac{-D_i}{H_i} & \frac{1}{H_i} & 0 & \frac{-1}{H_i} \\ 0 & \frac{-1}{T_i} & \frac{1}{T_i} & 0 \\ \frac{-1}{R_i T_{gi}} & 0 & \frac{-1}{T_{gi}} & 0 \\ B_{ij} & 0 & 0 & 0 \end{bmatrix} \quad (7)$$

$$B_{ii} = [0 \ 0 \ 1/T_{gi} \ 0]^T \quad (8)$$

$$B_{ii}^d = [1/H_i \ 0 \ 0 \ 0]^T \quad (9)$$

where $i = 1, 2, \dots, n$; H_i is the inertia constant; D_i is the damping constant; T_i is the time constant of the turbine; R_i is the primary droop gain; T_{gi} is the time constant of governor; and B_{ij} is the synchronizing coefficient between control areas i and j .

$$A_{n1} = \begin{bmatrix} 0_{3 \times 1} & 0_{3 \times 3} \\ -B_{n1} & 0_{1 \times 3} \end{bmatrix} \quad (10)$$

$$A_{ij} = \begin{bmatrix} 0_{3 \times 3} & 0_{3 \times 1} \\ -B_{ij} & 0_{1 \times 3} \end{bmatrix} \quad i = 1, 2, \dots, n-1, j = i+1 \quad (11)$$

$$A_{1n} = \begin{bmatrix} 0_{1 \times 3} & 1/H_1 \\ 0_{3 \times 3} & 0_{3 \times 1} \end{bmatrix} \quad (12)$$

$$A_{ji} = \begin{bmatrix} 0_{3 \times 3} & 1/H_j \\ 0_{1 \times 3} & 0 \end{bmatrix} \quad j = 2, 3, \dots, n, i = j-1 \quad (13)$$

Considering only the frequency as the output variable, the aggregate output vector $\mathbf{Y}$ is given by:

$$\mathbf{Y} = \mathbf{C}\mathbf{X} \quad (14)$$

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_{11} & \mathbf{C}_{12} & \dots & \mathbf{C}_{1n} \\ \mathbf{C}_{21} & \mathbf{C}_{22} & \dots & \mathbf{C}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{C}_{n1} & \mathbf{C}_{n2} & \dots & \mathbf{C}_{nn} \end{bmatrix} \quad (15)$$

$$\mathbf{C}_{ii} = [1 \ 0 \ 0 \ 0] \quad (16)$$

$$\mathbf{C}_{ij} = [0 \ 0 \ 0 \ 0] \quad (17)$$

where $i = 1, 2, \dots, n$, $j \geq 1$, $j \neq i$.

The decomposed model for each area is obtained by decomposing the input vector $\mathbf{U}$ in (1) into the local input $\mathbf{u}_i$ and other area input $\mathbf{u}_i^c$ while keeping the local i^{th} model state $\mathbf{X}_i$ same as that of the centralized system, i.e., $\mathbf{X}_i = \mathbf{X} = [\mathbf{x}_1^c, \dots, \mathbf{x}_{i-1}^c, \mathbf{x}_i^l, \mathbf{x}_{i+1}^c, \dots, \mathbf{x}_n^c]^T$, where $\mathbf{x}_i^l$ is the vector of locally measurable states and $\mathbf{X}_i^c = [\mathbf{x}_1^c, \dots, \mathbf{x}_{i-1}^c, \mathbf{x}_{i+1}^c, \dots, \mathbf{x}_n^c]^T$ is the vector of all the states in rest of the areas. The decomposed model is then given by:

$$\dot{\mathbf{X}}_i = \underbrace{\mathbf{A}_{c_i}}_{\text{System states}} \mathbf{X}_i + \underbrace{\mathbf{B}_{c_i} \mathbf{u}_i}_{\text{Local input}} + \underbrace{\mathbf{B}_{c_i}^c \mathbf{u}_i^c}_{\text{External input}} + \underbrace{\mathbf{B}_{c_i}^d \mathbf{d}}_{\text{Load disturbance}} \quad (18)$$

where $\mathbf{A}_{c_i} = \mathbf{A}$; $\mathbf{B}_{c_i}^d = \mathbf{B}^d$; $\mathbf{B}_{c_i}^c$ is the matrix of columns of $\mathbf{B}_c$ corresponding to $\mathbf{u}_i^c$; and $\mathbf{B}_{c_i} = [\mathbf{0}, \dots, \mathbf{0}, \mathbf{B}_{ii}, \mathbf{0}, \dots, \mathbf{0}]^T$; $i = 1, 2, \dots, n$.

The output is given by:

$$\mathbf{y}_i = \mathbf{C}_i \mathbf{X}_i \quad (19)$$

where $\mathbf{C}_i = [\mathbf{0}, \dots, \mathbf{0}, \mathbf{C}_{ii}, \mathbf{0}, \dots, \mathbf{0}]$. A discrete state space model of (18) and (19) is given by:

$$\mathbf{X}_i(k+1) = \mathbf{A}_i \mathbf{X}_i(k) + \mathbf{B}_i \mathbf{u}_i(k) + \mathbf{B}_i^c \mathbf{u}_i^c(k) + \mathbf{B}_i^d \mathbf{d}(k) \quad (20)$$

$$\mathbf{y}_i(k) = \mathbf{C}_i \mathbf{X}_i(k) \quad (21)$$

where k is the sampling interval.

The output prediction equation over the prediction horizon N_p is given by [21]:

$$\mathbf{y}_i(k+N_p|k) = \mathbf{F}_i \mathbf{X}_i(k|k) + \Phi_i \mathbf{u}_i(k+N_p|k) + \Gamma_i^c \mathbf{u}_i^c(k|k) + \Psi_i \mathbf{d}(k) \quad (22)$$

The computational matrices $\mathbf{F}_i$, Φ_i , Γ_i^c and Ψ_i , which are used to predict the free response of the outputs as given in (22), are computed off-line [23].

The SCDMPC formulation consists of an objective function (23), which minimizes the frequency deviation $\Delta \mathbf{f}_i = \mathbf{y}_i$ from its reference value as well as the governor input $\mathbf{u}_i$. Such an objective function is defined as:

$$\begin{aligned} J_\epsilon^* = \min & J(\mathbf{u}_i(k+N_p|k), \epsilon_i(k+N_p|k)) = \\ & \min \left(\underbrace{\frac{1}{2} \sum_{l=0}^{N_c-1} \|\mathbf{u}_i(l+k|k)\|_{\bar{\mathbf{u}}_i}^2}_{\text{Minimize governor input}} + \underbrace{\frac{1}{2} \sum_{l=1}^{N_p-1} \|\epsilon_i(l+k|k)\|_{\bar{\mathbf{u}}_i}^2}_{\text{Minimize } \Delta \mathbf{f}_i \text{ error}} \right. \\ & \left. \underbrace{\|\epsilon_i(N_p+k|k)\|_{\bar{\mathbf{u}}_i}^2}_{\Delta \mathbf{f}_i \text{ error at } k+N_p} \right) \end{aligned} \quad (23)$$

where $\epsilon_i(l+k|k) = \mathbf{Ref}_i - \mathbf{y}_i(l+k|k)$ and $\mathbf{y}_i(l+k|k)$ satisfies (22), $l = 1, 2, \dots, N_p$; and N_c is the control horizon. The vector $\epsilon_i(k+N_p|k)$ represents the predicted output error $\epsilon_i = \mathbf{Ref}_i - \mathbf{y}_i$

over the future $k+N_p$ samples, computed at the current sample k . $\mathbf{Ref}_i$ is the output set point vector of 0 s over N_p samples for area i . $\bar{\mathbf{R}}$ is the positive semi-definite input penalty matrix and $\mathbf{Q}$ is the positive semi-definite error weighting matrix, which are computed off-line in such a way that the closed loop system is stable [10]. The sets of constraints consist of (24)-(26), which maintain the governor saturation limits, GRC and tie-line flow state within their operation limits, respectively.

$$\underline{\mathbf{u}}_i \leq \mathbf{u}_i(l+k|k) \leq \bar{\mathbf{u}}_i \quad l = 0, 1, \dots, N_c \quad (24)$$

$$\Delta \underline{\mathbf{u}}_i \leq \Delta \mathbf{u}_i(l+k|k) \leq \Delta \bar{\mathbf{u}}_i \quad l = 0, 1, \dots, N_c \quad (25)$$

$$\Delta \underline{\mathbf{P}}_{ij} \leq \Delta \mathbf{P}_{ij}(l+k|k) \leq \Delta \bar{\mathbf{P}}_{ij} \quad \forall j = 1, 2, \dots, N_i^j \quad (26)$$

where $\Delta \mathbf{P}_{ij}$ is the deviation in tie-line power flow between areas i and j and $\Delta \mathbf{P}_{ij} \in \mathbf{X}_i$ with $\mathbf{X}_i$ satisfying (20); N_i^j is the number of physically connected area i to j ; $\underline{\mathbf{u}}_i$ and $\bar{\mathbf{u}}_i$ are the lower and upper limits on governor saturation; $\Delta \underline{\mathbf{u}}_i$ and $\Delta \bar{\mathbf{u}}_i$ are the lower and upper limits on GRC; and $\Delta \underline{\mathbf{P}}_{ij}$ and $\Delta \bar{\mathbf{P}}_{ij}$ are the lower and upper limits on ij^{th} tie-line.

III. APPLICATION OF SCDMPC TO POWER NETWORK

An AGC scheme is often implemented using a WAC scheme in a power network as shown in Fig. 1 [25]. In WAC framework, individual control areas send information of local states measured by sensors to WAC and also receive a reference signal from WAC by means of a communication network. This reference signal is a local ACE signal in traditional AGC scheme.

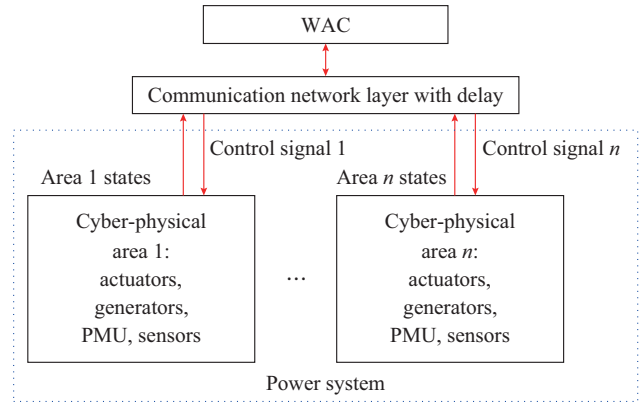


Fig. 1. AGC scheme in a WAC framework.

When the proposed SCDMPC scheme is implemented in a WAC framework, the communication network is responsible to share the information of the full system states $\mathbf{X}_i^c$ and input $\mathbf{u}_i^c(k)$ to each of the i^{th} control area at every control sample. Using the shared information, the full system state vector at k^{th} sample is obtained by rearranging and appending with the locally measured states $\mathbf{x}_i^l$ as $\mathbf{X}_m(k) = [\mathbf{x}_1^c, \dots, \mathbf{x}_{i-1}^c, \mathbf{x}_i^l, \mathbf{x}_{i+1}^c, \dots, \mathbf{x}_n^c]^T$ inside every local controller. The vector $\mathbf{X}_m(k)$ can then be used as $\mathbf{X}_i$ in (22) to predict the output over the prediction horizon. However, due to the communication network latency, the information of $\mathbf{X}_i^c$ and $\mathbf{u}_i^c$ can only be available with a few sample delays, which is the time lapsed between the local areas sending information to

WAC and then WAC sending the full system states and input information back to local areas, which is shown in Fig. 2 in red arrows.

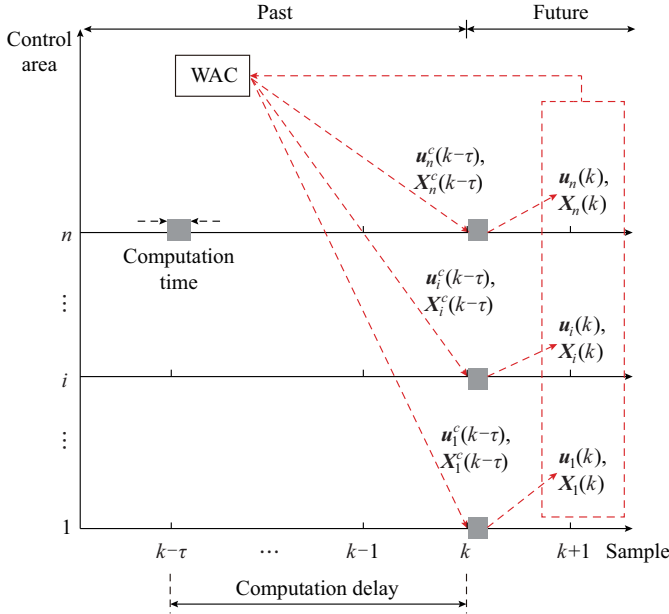


Fig. 2. SCDMPC coordination in WAC framework.

In Fig. 2, the coordination of information among distributed controllers for computation at sample k is shown. It is depicted that the state and input information of all areas is sent to the WAC at every sample soon after the computation and the controllers receive information of other area's states and inputs with a delay of τ samples at the start of computation. Due to the delay of τ samples, the prediction of states becomes erroneous if (22) is used without compensating for the delay. Secondly, in an actual system, since the feed-forward disturbance $\mathbf{d}(k)$ is unknown, the true estimation using (20) cannot be obtained and a compensation in state prediction is needed to account for it. Such limitations can disturb the coordination among distributed controllers and negatively impact the convergence. Finally, from the controller point of view, due to the presence of constraints on both the tie-line flow coupling states and governor inputs, the infeasibility can occur inside the SCDMPC solver under the large disturbances while solving (23)-(26). Again, convergence will not be obtained.

IV. PROPOSED ENHANCEMENT FOR SCDMPC SCHEME

To ensure the system level convergence, it is important for a distributed control scheme to have the proper coordination among all the distributed controllers. Under the assumption of τ sample delay for all the controllers, Fig. 2 shows the availability of system level information for any controller i at instant k . In order to account for this delay, a shifted prediction model is first developed and then a disturbance estimator is proposed to ensure the convergence. Finally, an infeasibility solver algorithm is proposed to address the limitations in the SCDMPC scheme discussed in Section III. The main assumptions of the algorithm are:

- 1) The computation time is less than the sample time so

that all the distributed controllers solve optimization problem simultaneously.

- 2) Same communication delay exists for all the control areas. This assumption is made only to keep the description simple.

- 3) The local states are measurable, and the system is observable.

A. Shifted Prediction to Handle Communication Delay

In this section, a shifted prediction model to account for the communication delay between WAC and local areas is developed so that the prediction accuracy is maintained. A model to account for communication delay is also proposed in [26], however, it does not use full system state in the local models and neglects the role of feed-forward disturbances in the prediction model.

Assume that each control area receives the control input and state information from WAC with a delay of $\tau > 0$ samples and that the local states and inputs are available without any delays. While neglecting the load disturbances and using (20), a one-sample ahead state prediction from sample τ can be given as:

$$\hat{\mathbf{X}}_i(k - \tau + 1) = \mathbf{A}_i \mathbf{X}_m(k - \tau) + \mathbf{B}_i \mathbf{u}_i(k - \tau) + \mathbf{B}_i^c \mathbf{u}_i^c(k - \tau) \quad (27)$$

As the local input $\mathbf{u}_i(k)$ is available for all the samples, a local buffer of past input moving from sample $k - \tau$ to $k - 1$ is maintained in each of the control areas. However, the information of $\mathbf{u}_i^c$ is only available until time instant $k - \tau$. Assuming $\mathbf{u}_i^c(k - \tau + l) = \mathbf{u}_i^c(k - \tau)$, $\forall l = 1, 2, \dots, \tau - 1$, (28) is iterated over τ samples starting from the $k - \tau$ sample to estimate the full system state $\hat{\mathbf{X}}_i(k)$ at the current sample k as:

$$\hat{\mathbf{X}}_i(k - \tau + l + 1) = \mathbf{A}_i \hat{\mathbf{X}}_i(k - \tau + l) + \mathbf{B}_i \mathbf{u}_i(k - \tau + l) + \mathbf{B}_i^c \mathbf{u}_i^c(k - \tau - 1) \quad (28)$$

The state estimation from (28) gives the predicted state value while correcting for the communication delay. However, the state estimation from (28) will have the error from the true state value, due to the unavailability of the feed-forward disturbances and the control signals $\mathbf{u}_i^c(k - \tau + 1), \dots, \mathbf{u}_i^c(k - 1)$. In order to account for these, a disturbance estimator is proposed in the next section.

B. Disturbance Estimation

In Section III-A, it has been explained that when the feed-forward disturbance $\mathbf{d}(k)$ is unknown in (20), (22) cannot be used to predict accurate states. Therefore, it is modified as (29) to obtain the estimated values of states without feed-forward disturbances.

$$\hat{\mathbf{X}}_i(k + 1) = \mathbf{A}_i \hat{\mathbf{X}}_i(k) + \mathbf{B}_i \mathbf{u}_i(k) + \mathbf{B}_i^c \mathbf{u}_i^c(k) \quad (29)$$

Consider that $\mathbf{C}_{o_i}$ is the output matrix corresponding to the locally measurable states of area i . The output is then defined as:

$$\mathbf{y}_i(k) = \mathbf{C}_{o_i} \mathbf{X}_i(k) \quad (30)$$

Assuming that $\mathbf{d}(k)$ is a signal representing the load disturbance, measurement noise and model uncertainties and satisfies:

$$\mathbf{d}(k + 1) = \mathbf{d}(k) \quad (31)$$

Then by using (31) and (20), the following augmented model for the disturbance estimator is obtained [27]:

$$\begin{cases} \mathbf{z}(k+1) = \mathbf{A}_o \mathbf{z}(k) + \mathbf{B}_o \mathbf{u}_i(k) + \mathbf{B}_o^c \mathbf{u}_i^c(k) \\ \mathbf{y}(k) = \mathbf{C}_o \mathbf{z}(k) \end{cases} \quad (32)$$

$$\begin{cases} \mathbf{A}_o = \begin{bmatrix} \mathbf{A}_i & \mathbf{B}_d \\ \mathbf{O}_1 & \mathbf{I} \end{bmatrix} \\ \mathbf{B}_o = [\mathbf{B}_i \quad \mathbf{O}]^T \\ \mathbf{B}_o^c = [\mathbf{B}_i^c \quad \mathbf{O}]^T \\ \mathbf{C}_o = [\mathbf{C}_i \quad \mathbf{O}] \end{cases} \quad (33)$$

where $i = 1, 2, \dots, n$; and $\mathbf{O}_1, \mathbf{O}, \mathbf{I}$ are the zero and identity matrices of compatible dimensions, respectively. The pair of matrices $(\mathbf{A}_o, \mathbf{C}_o)$ is observable under the assumption that $(\mathbf{A}_i, \mathbf{C}_i)$ is observable. Now, a full observer is designed to estimate the augmented state variable $\mathbf{z}(k)$ at the sample k . An observer gain $\mathbf{K}_{ob}$ is chosen such that the closed-loop observer error system $(\mathbf{A}_o - \mathbf{K}_{ob} \mathbf{C}_o)$ is stable with a desired response speed. Then, the augmented state variable $\mathbf{z}(k)$ is estimated using the following equation:

$$\hat{\mathbf{z}}(k+1) = \mathbf{A}_o \hat{\mathbf{z}}(k) + \mathbf{B}_o \mathbf{u}_i(k) + \mathbf{B}_o^c \mathbf{u}_i^c(k) + \mathbf{K}_{ob} (\mathbf{y}_i(k) - \mathbf{C}_o \hat{\mathbf{z}}(k)) \quad (34)$$

With the estimated state variable $\hat{\mathbf{z}}(k)$, the estimated signal $\hat{\mathbf{d}}(k)$ is obtained which is then used in the output prediction equation (22). The actual implementation of SCDMPC scheme with the proposed shifted prediction methodology and disturbance estimation in a WAC framework is shown in Fig. 3.

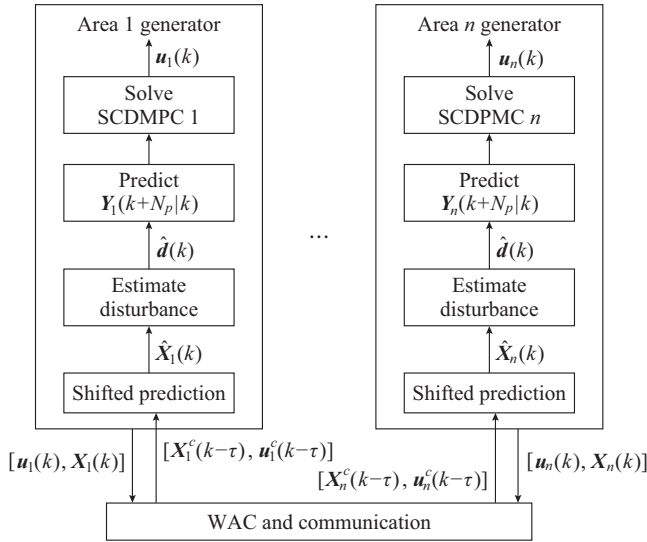


Fig. 3. SCDMPC implementation using WAC.

C. Infeasibility Handling by Constraint Softening

When the problem in (23)-(26) is feasible, the result $\mathbf{u}_i^*(l+k|k)$ is a vector of control moves, which satisfies the constraints in (24) and (26) for the system model given by (20) and (21). Out of the vector of control moves with size N_c , only the first move is implemented. However, an MPC formulation with state and input constraints can encounter infeasibility under large feed-forward disturbances. The traditional approach in MPC minimizes the constraint violations on the soft and less prioritized state constraints to recover from

dynamic infeasibility [24]. Such a methodology is limited when the problem size is of concern, even if the violations are tolerable. This paper proposes a strategy, which works by removing the tie-line state constraints but adds a reference of 0 on them, until the system recovers from infeasibility. Adding a set-point of 0 on tie-line flow deviations is in agreement with the AGC problem, because the feasible space of tie-line flow includes 0. Now, in order to set a reference on the constrained states, which are tie-line flow deviation, the output signal is selected to be ACE instead of only frequency by using the output matrix $\mathbf{M}$, given in (35). This approach does not increase the number of decision variables and hence keeps the computation time to a minimal.

$$\mathbf{y}_i^{ACE}(k) = \mathbf{M}_i \mathbf{X}_i(k) = \beta_i \Delta \omega_i + \Delta \mathbf{P}_{ij} - \Delta \mathbf{P}_{ri} \quad (35)$$

$$\mathbf{M} = \begin{bmatrix} \mathbf{M}_{11} & \mathbf{M}_{12} & \dots & \mathbf{M}_{1n} \\ \mathbf{M}_{21} & \mathbf{M}_{22} & \dots & \mathbf{M}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{M}_{n1} & \mathbf{M}_{n2} & \dots & \mathbf{M}_{nn} \end{bmatrix} \quad (36)$$

$$\mathbf{M}_{1n} = [0 \quad 0 \quad 0 \quad -1] \quad (37)$$

$$\mathbf{M}_{ij} = [0 \quad 0 \quad 0 \quad -1] \quad (38)$$

$$\mathbf{M}_{ii} = [\beta_i \quad 0 \quad 0 \quad 1]^T \quad (39)$$

where $i = 2, 3, \dots, n, j = i-1$; $\mathbf{M}_i$ is the i^{th} row of matrix $\mathbf{M}$; β_i is a positive frequency bias for area i ; and $\mathbf{y}_i^{ACE}$ is the ACE for area i . Switching the system output from Δf_i to ACE_i converts the state constraint problem in (23)-(26) into the traditional DMPC-based ACE regulation problem [15]-[18]. This formulation does not have constraints on coupling variables and is given in (40). The use of ACE as the control variable is widely accepted in traditional AGC, as it regulates both frequency and tie-line flow deviations to 0. Whenever any of the optimization solvers in the distributed controllers encounter infeasibility, an alarm is raised and the controller switches to the ACE-based formulation for the current sample control decision computation as shown in Algorithm 1. Note that this does not require any change in the controller structure and the decision variables remain the same.

$$\begin{cases} \mathbf{J}_s^* = \min J(\mathbf{u}_i(k+N_c|k), \delta_i(k+N_p|k)) = \\ \min \left\{ \underbrace{\frac{1}{2} \sum_{l=0}^{N_c-1} \|\mathbf{u}_i(l+k|k)\|_{\mathbf{B}}^2}_{\text{Minimize governor input}} + \underbrace{\frac{1}{2} \sum_{l=1}^{N_p-1} \|\delta_i(l+k|k)\|_{\mathbf{Q}}^2}_{\text{Minimize ACE}_i} + \right. \\ \left. \|\delta_i(N_p+k|k)\|_{\mathbf{N}_p}^2 \right\} \\ \text{s.t. (24), (25)} \end{cases} \quad (40)$$

where $\delta_i(l+k|k) = \text{Ref}_i - \mathbf{y}_i^{ACE}(l+k|k)$, $l = 1, 2, \dots, N_p$. The limits on the governor inputs in (25) are defined by choosing the tighter bound between the steam turbine and governor valve. The vector $\delta_i(k+N_p|k)$ has calculated values of the predicted error in $\mathbf{y}_i^{ACE}$ for next N_p samples calculated at current sample k . The above objective in (40) minimizes the ACE deviation as well as the governor input.

D. SCDMPC Algorithm

The computation steps of the SCDMPC scheme are given in Algorithm 1, which comprise an initialization part and a computation part. The computation part consists of a shifted prediction model to accommodate communication delay, a disturbance estimator, an output prediction block, an optimizer to solve the SCDMPC problem and an infeasibility solver. The interaction with WAC happens during the steps of sharing and gathering information.

Algorithm 1: SCDMPC algorithm with infeasibility solver

Initialize WAC and individual controllers, i.e., $X_m(k)$, $X_i(k)$, $u_i(k)$,

$u_i^c(k)$, $d(k)$

Initialize a vector of size τ for u_i^c and u_i in each area i for buffer

for $k=1$ to simulation time **do**

for $i=1$ to n **do**

 gather $X_m(k-\tau)$, $u_i^c(k-\tau)$ from WAC

 measure $x_i^l(k)$

 store buffer $[u_i(k-\tau), \dots, u_i(k-1)]$

end for

for $i=1$ to n **do**

 solve (27) and (28)

 solve (34) to obtain $\hat{d}_i$

 predict y_i by solving (22)

 solve problem in (23)-(26)

if infeasible **then**

 solve problem in (40)

end if

 update control move $u_i^*(k)$

$i \leftarrow i+1$

end for

for $i=1$ to n **do**

 implement $u_i^*(k)$ in subsystem i

 measure $x_i^l(k)$

 share $u_i^*(k)$ and $x_i^l(k)$ with WAC

end for

$k \leftarrow k+1$

end for

V. NUMERICAL STUDIES

A three-area power network as shown in Fig. 4 is used for the numerical studies with a sampling time of 0.2 s.

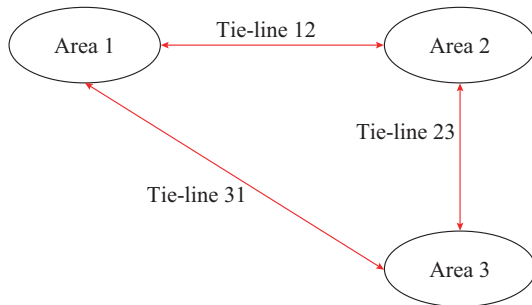


Fig. 4. Three-area interconnected power system.

The system parameters are given in Table AI [18] and simulation scenarios are described below:

1) Scenario 1 has disturbance patterns as shown in Fig. 5(a), which are designed to showcase the control capability of self-smoothing, optimization and bias free response of the SCDMPC formulation in presence of communication delay of 2 time samples and infeasibility.

2) Scenario 2 considers more realistic disturbances that arise with the integration of RESs. The wind speed fluctua-

tion data is taken from [31] and a DFIG dynamic model is simulated to get the wind output fluctuations.

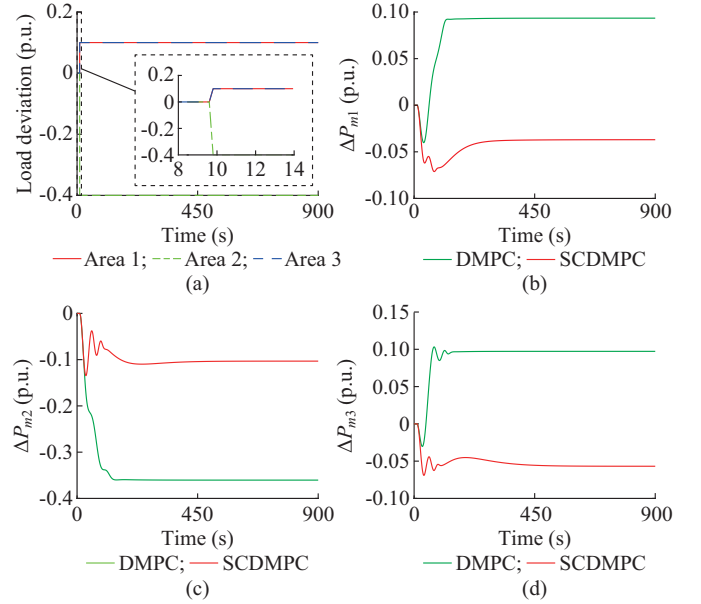


Fig. 5. Disturbance and deviation in turbine power of Scenario 1. (a) Disturbance. (b)-(d) Deviation in turbine power.

The dynamics of each area is modeled by (20) and (21), with the estimator in (34). The model data is given in Table AI. The performance of the proposed SCDMPC methodology in (23) - (26) is compared with the traditional DMPC scheme given in (40). To solve the quadratic optimization problem, the Hildreth programming in [29] is used.

VI. RESULTS DISCUSSION

A. Scenario 1

The results for Scenario 1 are shown in Figs. 5-7. The system is in steady state until $t=10$ s, when the disturbance occurs after which it undergoes a transient. From Fig. 6(a), it is evident that in both SCDMPC and DMPC schemes, it takes the approximately same time for the transients to settle. However, at the steady state, the frequency response is bias-free in SCDMPC scheme but not in DMPC scheme. The biased response in DMPC scheme occurs because the load loss in Area 2 is more than the lower operation limit for the steam turbine in the area, and hence the local controller cannot fully compensate for the load loss. However, in the case of SCDMPC scheme, the interconnected areas share power optimally via tie-lines as shown in Fig. 6(b) - (d), where Area 2 exports power to Areas 1 and 3 as ΔP_{12} becomes negative and ΔP_{23} becomes positive. This inter-area exchange of power maintaining tie-line flow thermal limits not only compensates the changes in the load but also minimizes the effort of individual control area as seen in the plots of turbine power output in Fig. 5(b) - (d). The plots clearly indicate that in all the control areas, the turbine power output deviation is much smaller in SCDMPC scheme compared with DMPC scheme, which follows local load disturbance. The total control action in three areas in both schemes is only -0.2 p.u., but individual control actions in

SCDMPC scheme are minimum. This is also shown in Fig. 7 (a)-(c). During this simulation, the SCDMPC scheme encounters infeasibility during the initial transients after $t=10$ s, which leads to an increased cost function momentarily as shown in Fig. 7(d). However, it recovers successfully by switching to the formulation in (40) and the tie-line flows settle within their bounds after 12 s.

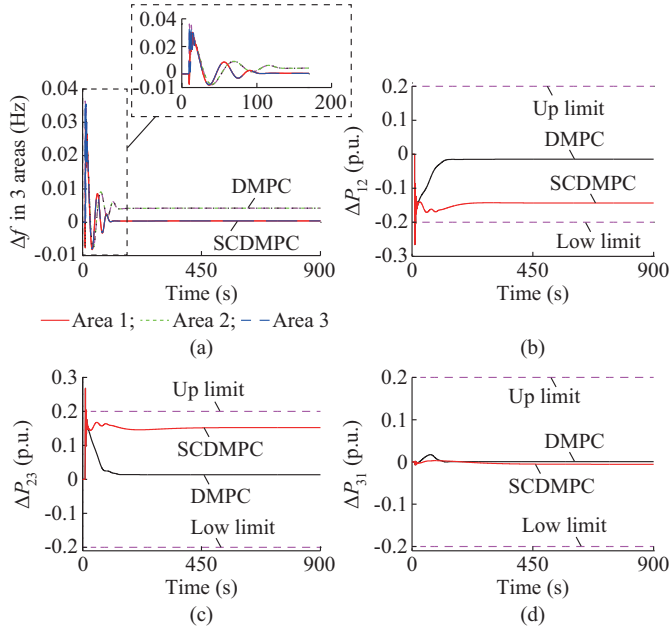


Fig. 6. Frequency and deviation in Scenario 1. (a) Frequency in Areas 1, 2 and 3. (b)-(d) Deviation in tie-line power flow.

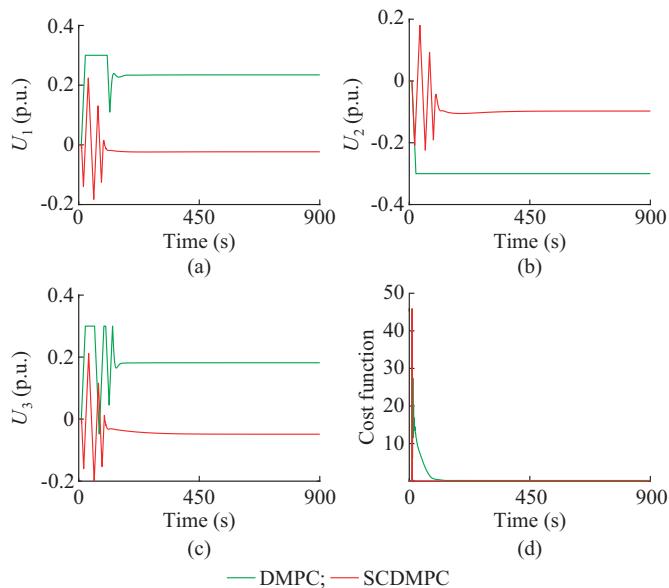


Fig. 7. Input moves and cost function in Scenario 1. (a)-(c) Input moves in Areas 1, 2 and 3. (d) Cost function over 900 s.

To summarize, in the SCDMPC scheme with shifted prediction, disturbance estimations and infeasibility solver, the control effort in each area does not have to match the local disturbances, rather the total sum of load disturbances in all the areas has to be matched with the total generation change. The potential of this methodology in smoothing out the dis-

turbance by sharing power in real time among the areas is thus confirmed. The total cost function in all areas for a simulation time of 900 s is given in Fig. 7(d). The total cost function for 900 samples in SCDMPC formulation based on (23) was only 4.1% of the cost function of the DMPC scheme using ACE regulation (40) as shown in Fig. 7(d). The computation time and infeasibility flags are shown in Fig. 8.

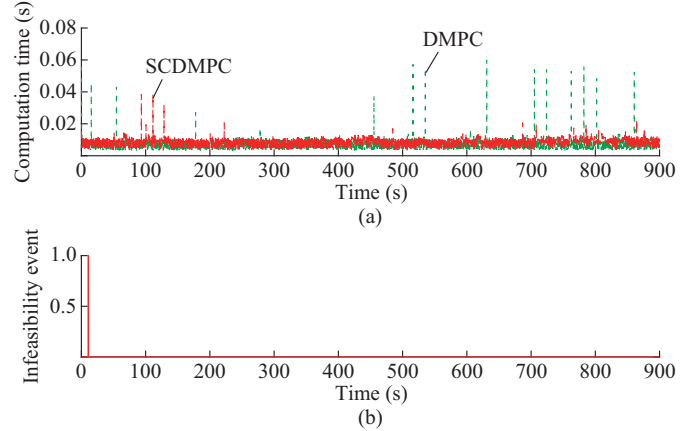


Fig. 8. Performance parameters for Scenario 1. (a) Computation time. (b) Infeasibility flags.

B. Scenario 2

The results for Scenario 2 are given in Figs. 9-11.

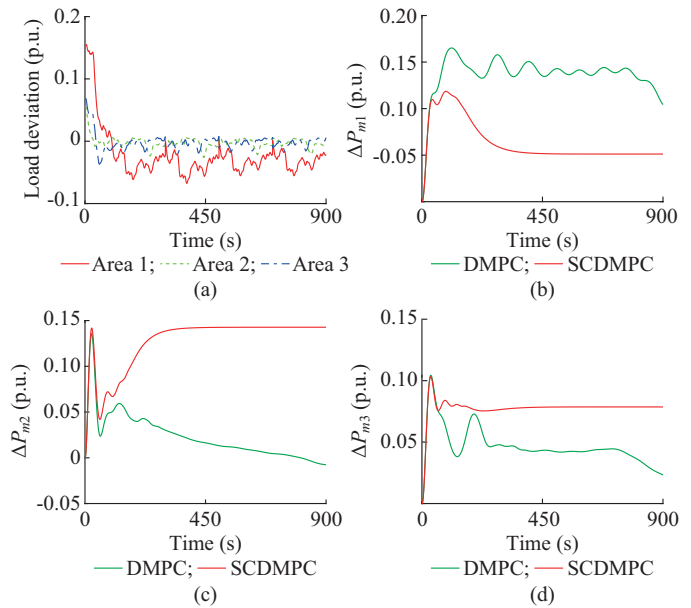


Fig. 9. Disturbance and deviation in Scenario 2. (a) Disturbance. (b)-(d) Deviation in turbine power.

As expected with the RES generation fluctuations, the SCDMPC methodology regulates the frequency deviation as shown in Fig. 10(a) with much less fluctuations in control efforts as shown in Fig. 11(a)-(c). This leads to a smaller cost function as shown in Fig. 11(d). The total cost function for 900 samples in the SCDMPC case is only about 6% of the total cost function in the existing ACE-regulation-based DMPC methodology. This has been possible due to real-time power sharing between areas as shown in the tie-line flow plots

as shown in Fig. 10(b)-(d). Since the tie-lines never cross the bounds, there is no infeasibility encountered in this scenario.

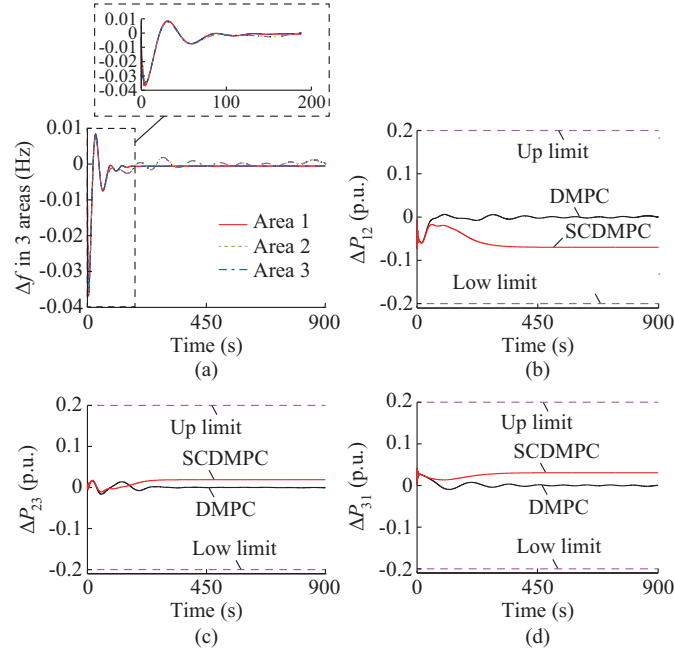


Fig. 10. Frequency and deviation in Scenario 2. (a) Frequency in Areas 1, 2 and 3. (b)-(d) Deviation in tie-line power flow.

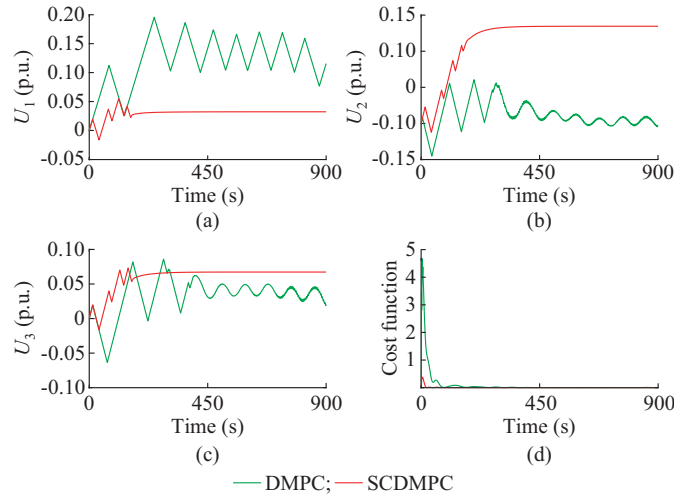


Fig. 11. Input moves and cost function in Scenario 2. (a)-(c) Input moves in Areas 1, 2 and 3. (d) Cost function over 900 s.

Based on the theoretical discussions and the above results, a qualitative comparison of SCDMPC with DMPC schemes is given in Table I.

TABLE I
GENERATION AND SCDMPC PARAMETERS

Parameter	SCDMPC	DMPC
Settling time in Scenario 1 (s)	100	110
Steady-state error in Scenario 1 (Hz)	0	0.004
Control effort in Scenario 1/ Scenario 2	4.1%/6%	100%/100%
Network utilization	Optimal within thermal limits	Sub-optimal

VII. CONCLUSION

An optimal AGC strategy based on SCDMPC scheme is investigated for the application in an interconnected power network under the real-time operation conditions of communication delays and large demand disturbances. A shifted prediction methodology is developed to handle the communication delay and a disturbance estimator is proposed to account for the unmeasured feed-forward disturbances in the state estimation. An infeasibility solving algorithm is also proposed to handle the large disturbances, which leads to conflicting constraint situations. Two numerical studies are conducted to quantify the theoretical claims, which show that the control cost in SCDMPC is only 4% in Scenario 1 and 5.2% in Scenario 2 of the cost of traditional MPC scheme. The numerical studies demonstrate that the control scheme can recover successfully from infeasible scenarios when conflicting constraints occur. Overall, the proposed methodology shows the improved control, thermal, and cost performance with an added benefit of self-smoothing of disturbances across geographically distributed area. Such a methodology can pave the way for the integration of more RESs into the power network without increasing the need for regulation reserves.

APPENDIX A

TABLE AI
GENERATION AND SCDMPC PARAMETERS

Parameter	Value
Number of areas n	3
Prediction horizon N_p	60
Control horizon N_c	50
Droop characteristic R_i	[0.03, 0.07, 0.05]
Constraint in Area 1	$[\Delta P_{12}, \Delta P_{31}]$
Total damping D_i	[2.00, 2.75, 2.40]
Constraint in Area 3	$[\Delta P_{31}, \Delta P_{23}]$
Turbine time constant T_i	[50, 10, 30]
Tie-line power flow limit $[\underline{P}_{ij}, \bar{P}_{ij}]$	[-0.2, 0.2]
Total inertia H_i	[3.50, 4.00, 3.75]
Input constraint $[\underline{u}_i, \bar{u}_i]$	[-0.3, 0.3]
GRC constraint $[\Delta \underline{u}_i, \Delta \bar{u}_i]$	[-0.02, 0.02]
Frequency bias β_i	[3, 3, 3]
Output weight Q_i	[100, 100, 100]
Governor time constant T_{Gi}	[40, 25, 32]
Input penalty $\bar{R}$	[0.05, 0.05, 0.05]
Tie-line gain B_{ij}	[7.54, 7.54, 7.54]
Constraint in Area 2	$[\Delta P_{23}, \Delta P_{12}]$

APPENDIX B

In Theorem 1, the optimality of SCDMPC over the traditional DMPC is proven.

Theorem 1 If u_i and u_i^* are respectively the converged solution of (23)-(26) at the steady state, then $J_\epsilon^* \leq J_\delta^*$.

Proof Since u_i^* is the optimal solution of (24)-(26), it

will satisfy both $\Delta f_i = 0$, $\forall i = 1, 2, \dots, n$ and $\Delta P_{ij}^* = 0$, $\forall ij$: $a_{ij} = 1$. Hence, $\mathbf{u}_i^*$ is also a feasible but may not be the optimal solution of (23) - (26) as the region spanned by the bounds on tie-line, $\Delta \underline{P}_{ij}$ and $\Delta \bar{P}_{ij}$ include 0. Now if $\mathbf{u}_i^*$ is the optimal solution of (23)-(26), then it must satisfy:

$$\mathbf{J}_\epsilon(\mathbf{u}_i^*(k + N_c|k), \epsilon_i(k + N_p|k)) = \mathbf{J}_\epsilon^* \quad (\text{B1})$$

In case it does not satisfy (B1), by virtue of the optimization it must respect (B2) because $\mathbf{J}_\epsilon^*$ is the optimal.

$$\mathbf{J}_\epsilon(\mathbf{u}_i^*(k + N_c|k), \epsilon_i(k + N_p|k)) \geq \mathbf{J}_\epsilon^* \quad (\text{B2})$$

With (B1) and (B2), Theorem 1 is proved.

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Ragini Patel received the B.Eng. degree in electrical engineering from Government Engineering College, Rewa, India, in 1999, and the M.Tech. degree in systems and control engineering from the Indian Institute of Technology, Mumbai, India, in 2002. She received her Ph.D. degree from the Royal Melbourne Institute of Technology (RMIT) University, Melbourne, Australia, in 2018. She is currently working with GHD group Pty Ltd., Melbourne, Australia as a senior power system engineer. Her research interests include systems and control, model predictive control, optimization and control of power system under high penetration of renewable energy resources into power networks.

Lasantha Meegahapola received the B.Sc. Eng. degree in electrical engineering (First Class) from the University of Moratuwa, Moratuwa, Sri Lanka in 2006, and the Ph.D. degree from the Queen's University of Belfast, Northern Ireland, UK in 2010. His doctoral study was based on the investigation of power system stability issues with high wind penetration, and the research was conducted in collaboration with EirGrid (Republic of Ireland-TSO). He was a visiting researcher in the Electricity Research Centre, University College Dublin, Dublin, Ireland in 2009-2010. From 2011-2014, he was employed as a Lecturer at the University of Wollongong (UOW), Wollongong, Australia, and continues as an honorary fellow at UOW. He is currently employed as a Senior Lecturer at the RMIT University, Melbourne, Australia. He is a Senior Member of IEEE and a Member of the IEEE Power Engineering Society. He has over 12 years research experience in power system dynamics and stability with renewable power generation and has published more than 80 journal and conference articles. He has also conducted research studies on microgrid dynamics & stability and coordinated reactive power dispatch during steady-state and dynamic/transient conditions for networks with high wind penetration.

Liuping Wang received the Ph.D. degree from the University of Sheffield, Sheffield, UK. Upon completion of her Ph.D. degree, she worked at the University of Toronto, Toronto, Canada for eight years in the field of process control. From 1998 to 2002, she worked at the University of Newcastle, Newcastle, Australia. In February 2002, she joined RMIT University, Melbourne, Australia where she is a Professor of Control Engineering since 2007. She has authored and co-authored more than 200 scientific papers in the field of systems and control. She co-authored a book with Professor Cluett entitled “From process data to process control - ideas for process identification and PID control” (Taylor and Francis, 2000). She co-edited two books with Professor Garnier entitled “Continuous time model identification from sampled data” (Springer-Verlag, 2008) and “System identification, environmental modelling and control” (Springer-Verlag, 2011). Her book entitled “Model predictive control design and implementation using MATLAB®” was published by Springer-Verlag in 2009. She is the lead author of the book entitled “PID and predictive control of electrical drives and power converters using MATLAB®” (Wiley-IEEE, 2015). Her new book is entitled “PID control system design and automatic tuning using MATLAB/Simulink” (Wiley-IEEE, 2019).

Xinghuo Yu is Associate Deputy Vice-Chancellor and Distinguished Professor of RMIT University, Melbourne, Australia. He received the B.Eng. and M.Eng. degrees in electrical and electronic engineering from the University of Science and Technology of China, Hefei, China, in 1982 and 1984, and Ph.D. degree from Southeast University, Nanjing, China in 1988, respectively. He started his academic career in 1989 as a Postdoctoral Fellow at the

University of Adelaide, Adelaide, Australia. In 1991, he joined Central Queensland University, Australia, where, before he left in 2002, he was Professor of Intelligent Systems and Associate Dean (Research) of Faculty of Informatics & Communication. Since 2002, he has been with RMIT University, where he has held various managerial positions such as Associate Dean and Research Institute Director. He received a number of awards and honours for his contributions, including the 2013 Dr.-Ing. Eugene Mittelmann Achievement Award of IEEE Industrial Electronics Society and 2018 M. A. Sargent Medal of Engineers Australia (the Institution of Engineers, Australia). He was named a Highly Cited Researcher by Clarivate Analytics (formerly Thomson Reuters) in 2015-2018. He is President of IEEE Industrial Electronics Society for 2018 and 2019. He is a Fellow of the IEEE and several other professional societies. His research interests include control systems, intelligent and complex systems, and smart energy systems.

Brendan McGrath received the B.E. degree in electrical and computer systems engineering in 1997, the B.Sc. degree in applied mathematics and physics in 1997, and the Ph.D. degree in 2003 from Monash University, Melbourne, Australia, respectively. He is with the School of Engineering at RMIT University, Melbourne, Australia. He has published over 140 journal and conference articles, and in 2004 was awarded the Douglas Lampard research medal from Monash University for his Ph.D. thesis. He is a member of the IEEE Power Electronics, Industry Applications and Industrial Electronics Societies, and is an associate editor for the IEEE Transactions on Power Electronics. His research interests include the modulation and control of power electronic converters.