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Distributed model predictive control for economic dispatch of power systems with high penetration of renewable energy resources

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ABSTRACT

Distributed generation entities such as renewable energy sources have posed great challenges on power system economic dispatch because of their output variability and stochasticity. Accordingly, operators need to lessen unpredictable changes in scheduled generation settings by fully utilizing available forecast information in the decision-making process. This paper proposes a closed-loop algorithm for solving economic dispatch at runtime while reducing potential deviations of generation schedules. At first, a traditional centralized approach that addresses the economic dispatch problem is presented with discussions on potential enhancement enabled by model predictive control (MPC) techniques. The MPC application makes it possible for operators to address the concern of variability and stochasticity. This paper develops a dual decomposition-based distributed model predictive control (DDMPC) strategy that is compatible with consensus techniques. Different advantages of the proposed DDMPC are highlighted throughout the paper and are analyzed through simulations. The simulation results validate the advantages of the proposed DDMPC approach by comparing it with traditional techniques for economic dispatch and by another distributed method based on MPC.

1. Introduction

Power system has been increasingly faced with challenges of generation variability as a multitude of renewable energy resources are accommodated in the power system operation. As a response to such uncertain operating condition, power system operators optimize the commitment and dispatch of generators for supplying the electricity demand while respecting all physical and operational requirements. Economic dispatch of generation resources is an optimization problem that aims to meet short-term (e.g., hourly, 15-min, 5-min) load requirements economically. Economic dispatch is commonly performed after the unit commitment (UC), which determines on/off statuses of generating units. Since the information for the UC calculation often experiences some real-time deviations (e.g., variability of renewable generating resources, load forecast errors, random equipment outages), economic dispatch is conventionally determined by operators that collect technical and operation information from participating generators, which necessitates a complex communication network architecture that could be costly for large-scale power systems.

On the contrary, distributed optimization methods have a simpler communication network need since generators are not required to keep communicating with operators for achieving the stated objectives. Moreover, a distributed optimization approach enables parallel optimization for reducing computation complexity and solution time. However, the design and implementation of a distributed optimization approach is challenging when dynamic behaviors of individual generators are coupled. Furthermore, it is difficult to calculate an optimal solution of economic dispatch when the sharing of operation information of individual generators is restricted.

In addition to selecting the appropriate control strategy and a certain type of dispatch architecture, power system operators consider possible scenarios pertaining to uncertain variables. These uncertain variables may have different effects on the economic dispatch constraints. Technical constraints are presented in both single-interval and multi-interval forms. The former constraints include the generating units capacity, hourly loads, and network security constraints. The latter constraints comprise ramp-rate limits, minimum on/off time, and energy-limited resources capacity (e.g., batteries). In addition, variable

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Nomenclature

General notations

$\boldsymbol{x}$	column vectors
x	scalar numbers
n	amount of generators
$\mathbb{1}_n$	column tile with n unitary entries
$\lvert\cdot\rvert$	cardinality of a set
k	sampling time discretized by Δt
$\widetilde{k}$	sampling time discretized by $\widetilde{\Delta} t$, where $\widetilde{\Delta} t \ll \Delta t$
$\check{k}$	sampling time discretized by $\check{\Delta} t$, where $\check{\Delta} t \to 0$.

Sets

$\mathscr{S}$	generators
$\mathscr{N}_\ell$	neighbors of generator $\ell \in \mathscr{S}$
$\mathscr{E}$	information links
$\mathbb{R}$	real numbers
$\mathbb{R}_{\geqslant 0}$	non-negative real numbers
$\mathbb{Z}_{\geqslant 0}$	positive integer numbers.

Notations for discrete time control

$J(\boldsymbol{P})$	cost function
$\boldsymbol{P}$	vector of control inputs $\boldsymbol{P} \in \mathbb{R}^n$
Q	power system load, $Q \in \mathbb{R}_{\geqslant 0}$
$\boldsymbol{P}_{k+j\mid k}$	prediction made at time k for the vector $\boldsymbol{P}$ at discrete time $k+j$, $\boldsymbol{P}_{k+j\mid k} \in \mathbb{R}^n$
$Q_{k+j\mid k}$	prediction made at time k for the load Q at discrete time $k+j$, $Q_{k+j\mid k} \in \mathbb{R}_{\geqslant 0}$
H_p	prediction horizon
$\mu_{\widetilde{k}}$	Lagrange multiplier at time instant $\widetilde{k}$
α	update weight
$\xi_{\ell,\check{k}}$	auxiliary variable for generator ℓ at time instant $\check{k}$
w_{ij}	weight of the link between nodes i and j.

Notations for economic dispatch

$P_{\ell,k}$	power produced by generator ℓ at instant k
$P_\ell^{\min}$	minimum power limit of generator ℓ
$P_\ell^{\max}$	maximum power limit of generator ℓ
$\Delta P_{\ell,k}$	slew rate of generator ℓ at instant k, i.e., $P_{\ell,k} - P_{\ell,k+1}$
$\Delta P_\ell^{\min}$	minimum slew rate of generator ℓ
$\Delta P_\ell^{\max}$	maximum slew rate of generator ℓ
a_ℓ	quadratic cost component of generator ℓ
b_ℓ	linear cost component of generator ℓ
$C_\ell(P_{\ell,k})$	production cost of generator ℓ
Q_k	load of the system at instant k
T	operation horizon
$\boldsymbol{\lambda}_k$	vector of Lagrange multipliers at instant k, $\boldsymbol{\lambda}_k \in \mathbb{R}^{H_p+1}$
λ_{k+j}	Lagrange multiplier at instant $k+j$
$\psi^m_{\ell,k+j}$	local Lagrange multipliers of generator ℓ at instant $k+j$ for $m = 1, \ldots, 4$
$\boldsymbol{z}_\ell$	vector of auxiliary variables for the dual decomposition algorithm, $\boldsymbol{z}_\ell \in \mathbb{R}^{H_p+1}$
$\boldsymbol{Z}_{\widetilde{k}}$	matrix of auxiliary variables of all generators, at instant $\widetilde{k}$, $\boldsymbol{Z}_{\widetilde{k}} \in \mathbb{R}^{H_p+1\times n}$
$\boldsymbol{q}_k$	vector of load prediction at instant k, $\boldsymbol{q}_k \in \mathbb{R}^{H_p+1}$
$\boldsymbol{\varepsilon}_{\widetilde{k}}$	vector of auxiliary variables for calculating $\boldsymbol{\lambda}_k$ at instant $\widetilde{k}$, $\boldsymbol{\varepsilon}_{\widetilde{k}} \in \mathbb{R}^{H_p+1}$
$\boldsymbol{\xi}_{\ell,\check{k}}$	vector of auxiliary variables for generator ℓ at instant $\check{k}$
$k+j\mid k$	variable with this subscript denotes its predicted amount at instant $k+j$ and the prediction is made at instant k.

resources (e.g., wind, hydro, solar) are introducing new challenges to power system operators. By using forecasting models and optimization schemes that consider stochastic scenarios, power system operators strive to commit or dispatch thermal plants that can balance variable power supplies and minimize operating costs [1].

In this paper, we consider a model predictive control (MPC) design for calculating the centralized economic dispatch for power systems in a distributed manner. MPC methods have been successfully applied to common industrial applications like process control. MPC applications in power systems have been intensified within the last few years, given the increasing implementation of distributed generation technologies such as roof-top solar panels and local energy storage devices. MPC studies on the power system economic dispatch problem include both centralized and distributed control strategies.

Regarding centralized approaches, Abdeltawab et al. in [2] have proposed an energy management system for a hybrid power system with wind generation and energy storage. In this approach, they maximize the benefit of a hybrid system with forecasts for wind speed and energy prices. MPC was considered by Kim et al. in a dynamic economic dispatch approach [3]. The authors include a capacity constraint for the wind energy by considering a Weibull distribution. In [4], Zhu et al. have proposed a switched MPC model, for managing photovoltaic systems with storage devices, which considers switched constraints instead of a switched state space model. Mayhorn et al. [5] have proposed an MPC to integrate wind power plants by using a combined diesel generator and an energy storage system for coordination. A game theory-based demand response approach is proposed and analyzed by Nwulu et al. in [6]. The approach use demand response incentives in the optimal economic and emission dispatch problems. In [7], Torreglosa et al. present an energy dispatch based on MPC for an off-grid hybrid system with hydrogen storage. The MPC obtains the optimal hourly hydrogen power to be delivered or absorbed, considering the system constraints. Zheng et al. in [8] have developed a heuristic MPC with a differential evolution algorithm to manage an energy storage system. Palma-Behnke et al. in [9] have proposed a centralized MPC-based energy management system that minimizes operation costs in a microgrid. Garcia-Torres et al. in [10] have proposed a centralized MPC-based economic dispatch of microgrids with external agents and electric vehicles. Energy exchange among the microgrid and external agents is based on economic benefits received in comparison with its individual behavior. In [11], Acevedo-Arenas et al. have provided an energy management system to minimize operational costs of a microgrid composed by renewable generators and demand response. They use levelized costs of energy in a centralized dispatch where energy excess is delivered to the grid. A two-stage stochastic economic dispatch based on MPC in order to include renewables uncertainty from a centralized perspective has been developed by Alqurashi et al. in [12], but curse of dimensionality may arise in large-scale systems. Arasteh et al. [13] have addressed the optimal operation of market-based operation of power systems including energy storage and demand response. The authors use Markov chains and Montecarlo methods to include variability of wind by maximizing social welfare.

Considering distributed approaches, Ilić et al. in [14] proposed a method known as DYMONDS, which has both centralized and distributed features. The authors have showed that a fully distributed algorithm may not reach a balance between generation and demand. The authors applied MPC to solve economic and environmental dispatch problems with intermittent generation resources [15]. Del Real et al. in [16] designed a distributed MPC based on Lagrange-MPC. The proposed optimization problem minimized both economic and environmental costs in interconnected energy hubs. In [17,18], there is a discussion on the distributed model of predictive control. As an alternative, [19] presents a decomposition of the whole problem into smaller decoupled problems and the corresponding coordination performed in a centralized manner. Zheng et al. in [20] have proposed an energy management system that accounts for the minimization of operation costs, environment damage, peak load, and load curve volatility. Authors separate and solve these problems independently without considering ramp-rate limits. An economic model predictive control to address power systems operation from a dynamic perspective has been proposed by Kohler et al. in [21]. The authors define an optimization problem that minimizes costs through the alternating direction method of multipliers while reducing frequency deviations. However, they do not include renewable power plants and ramp-rate limits.

Among distributed approaches based on different methods, Wang et al. in [22] have proposed a decentralized optimization method based on penalty function in order to minimize operation costs by distributing loads. A mathematical optimization approach to solve economic dispatch via semidefinite programming has been proposed by Gil et al. in [23]. In [24], Kouveliotis et al. have provided a distributed economic dispatch based on replicator dynamics that minimizes operation costs and power losses. Lin et al. in [25] have developed a coordinated economic dispatch of transmission and distribution networks by using a modified generalized benders decomposition. A hierarchical economic dispatch of thermal generator by using clusters and leader–follower multiagent system have been designed by Guo et al. in [26]. Lu et al. in [27] have proposed a frequency control approach combined with economic dispatch. They minimize operation costs and frequency deviation by using a multiagent system and incremental costs consensus. In [28], Li et al. have designed a distributed economic dispatch that balances the system through frequency control. They use consensus, PI controllers and neural networks. Xia et al. in [29] have proposed a distributed economic dispatch for islanded microgrids by using two communication graphs and defining control laws that ensure energy balance.

To the best of our knowledge, distributed approaches that do not rely on MPC lack of some important features. Dynamic optimization and ramp-rate limits are not considered often, full information might be required, slow convergence may arise, and in some cases renewable plants and energy storage are not included. On the other hand, there are some points that are not addressed by existing distributed MPC methods when applied for economic dispatch, such as the quality of solution compared to a centralized MPC and granularity of agents.

In this paper, we propose a distributed approach for solving the economic dispatch problem in order to tackle the curse of dimensionality commonly seen in centralized stochastic approaches. The distributed MPC (DDMPC) uses dual decomposition along with an average consensus algorithm. Since a fully distributed approach without a coupling balance constraint will deviate from an appropriate operation point [14], one of the main contributions of this research is to balance power generation and load demand in a distributed approach that emulates the centralized solution. A centralized solution is recognized as the benchmark because of the existence of a central controller with full information [14]. Emulation of the centralized dispatch is a complicate task since generators might require other generators' unpublished cost and production data. In an MPC approach, we provide a distributed economic dispatch solution with a coupling balance constraint which will not require any private information, as another important contribution of this work. The proposed formulation is solved by every power plant in the network such that granularity of agents is enhanced. Contributions and main benefits of this research can be summarized as: (i) distributed emulation of a centralized MPC; (ii) achieving economic balance in a distributed manner; (iii) very high granularity of agents; (iv) economic integration of renewables in online operation of power systems; (v) assessment of renewable impact on ramp-rate limits; (vi) MPC to hedge variables volatility in large-scale power systems; and (vii) feasibility of short-term dispatch even for very large power systems.

The remainder of this paper is organized as follows. In Section 2 the background of MPC, dual decomposition, and distributed dual decomposition is provided. Section 3 describes the problem statement for both centralized and distributed approaches. The results of case studies are presented in Section 4, along with a justification of why it is better to use MPC instead of traditional approaches. Finally, in Section 5 conclusions are drawn.

2. Problem formulation and mathematical background

Power system operators dispatch generators economically in order to satisfy the load at every time step. In the economic dispatch problem, consider n generators in the set $\mathscr{S} = \{1, \dots, n\}$, with individual generation limits $P_\ell^{\min}$ and $P_\ell^{\max}$, and ramping restrictions $\Delta P_\ell^{\min}$ and $\Delta P_\ell^{\max}$, where $\ell \in \mathscr{S}$. A time-variant load Q that must be satisfied by minimizing total generation costs calculated by $\sum_{\ell=1}^{n} C_\ell(P_{\ell,k}) = \sum_{\ell=1}^{n} a_\ell P_{\ell,k}^2 + b_\ell P_{\ell,k}$.

2.1. Model predictive control

Consider a control objective of minimizing the cost function $J(\boldsymbol{P})$. The dispatch of generators is controlled by an MPC controller that optimizes the following optimization problem subject to a set of constraints $\mathscr{P}$:

$$\underset{\boldsymbol{P_{k+j|k}}}{\text{minimize}} \sum_{j=0}^{H_p} J(\boldsymbol{P}_{k+j|k}). \tag{1}$$

The solution of (1) corresponds to an optimal control input sequence given by $\widehat{\boldsymbol{P}}_k^\star \triangleq (\boldsymbol{P}_{k|k}^\star, \boldsymbol{P}_{k+1|k}^\star, \dots, \boldsymbol{P}_{k+H_p|k}^\star)$. Since only one control input from the sequence $\widehat{\boldsymbol{P}}^\star$ is applied to the power system operation at each time step, the final optimal control action at time step k is given by $\boldsymbol{P}_k^\star \triangleq \boldsymbol{P}_{k|k}^\star \in \mathscr{P}$. Once the optimal control input $\boldsymbol{P}_k^\star$ takes effect and new information of the system operating state is obtained, a new optimization problem in the form of (1) is solved for time step $k+1$, which leads to a new optimal sequence. This process continues until operation termination.

2.2. Dual decomposition

Dual decomposition is performed by utilizing the Lagrangian function corresponding to the original optimization problem [30]. Consider an optimization problem $\text{minimize}_{\boldsymbol{P}} J(\boldsymbol{P})$ with a coupled constraint $\sum_{\ell=1}^{n} P_\ell = Q$. Then, the Lagrangian function with mapping $L: \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}$ is defined as

$$L(\boldsymbol{P}, \mu) = J(\boldsymbol{P}) + \mu\left(\sum_{\ell=1}^{n} P_\ell - Q\right), \tag{2}$$

where $\mu \in \mathbb{R}$ is the Lagrange multiplier associated with the coupled constraint. The dual decomposition iterative procedure is then stated as:

$$\boldsymbol{P}_{\widetilde{k}+1} = \underset{\boldsymbol{P}_{\widetilde{k}}}{\text{argminimize}}\, L(\boldsymbol{P}_{\widetilde{k}}, \mu_{\widetilde{k}}), \tag{3a}$$

$$\mu_{\widetilde{k}+1} = \mu_{\widetilde{k}} + \alpha\left(\sum_{\ell=1}^{n} P_{\ell,\widetilde{k}+1} - Q\right), \tag{3b}$$

where α is a convergence parameter. For convenience, Eq. (3b) is rewritten as:

$$\mu_{\widetilde{k}+1} = \mu_{\widetilde{k}} + \alpha(\boldsymbol{P}_{\widetilde{k}+1}^\top \mathbb{1}_n - Q). \tag{4}$$

To start the procedure, the value of the Lagrange multiplier is initialized in the feasible range $\mu_0 \in \mathbb{R}$. Then, the optimization problem

(3a) is solved to find $\boldsymbol{P}_{\tilde{k}+1}$ so as to update the Lagrange multiplier through (3b). Eqs. (3a) and (3b) are solved iteratively until convergence is satisfied. Since $\widetilde{\Delta}t \ll \Delta t$, the Lagrangian iterative process is always performed before new information of the system is available.

2.3. Distributed dual decomposition algorithm

Consider a connected and undirected communication graph denoted by $\mathscr{G} = (\mathscr{S}, \mathscr{E})$, where each node (generator) is designated a decision variable denoted by P_ℓ. As can be proved by graph theory, the existence of the coupled constraint (3b) will result in a centralized dual decomposition algorithm, i.e., all information from $P_{\ell,\tilde{k}+1}$, for all $\ell \in \mathscr{S}$, will be required to update the Lagrange multiplier $\mu_{\tilde{k}+1}$. However, for an optimization problem with a specific coupled constraint, it is possible to implement the dual decomposition algorithm (3) in a distributed manner. The main idea is to add an additional step in the dual decomposition algorithm in order to compute $\sum_{\ell=1}^{n} P_{\ell,\tilde{k}+1}$ from a distributed perspective. The distributed algorithm would have the following steps: (i) solve the Lagrangian dual subproblem (3a), (ii) find $\sum_{\ell=1}^{n} P_{\ell,\tilde{k}+1}$ with an average-consensus algorithm, and (iii) update the Lagrange multiplier (3b).

The following average-consensus algorithm is considered for our study. Let $\boldsymbol{\xi} \in \mathbb{R}^n$ be a vector of auxiliary variables, i.e., $\xi_\ell \in \mathbb{R}$ corresponding to a node $\ell \in \mathscr{S}$. The variables are initialized according to the results obtained from (3a), i.e., $\xi_{\ell,0} = P_{\ell,\tilde{k}+1}$, for all $\ell \in \mathscr{S}$. Next, a discrete-time standard average consensus algorithm is performed iteratively until convergence is achieved (convergence proofs of the algorithm are addressed by Xiao et al. in [31]). The consensus equation is defined as:

$$\xi_{\ell,\check{k}+1} = \xi_{\ell,\check{k}} + \sum_{i \in \mathscr{N}_\ell} w_{\ell i}(\xi_{i,\check{k}} - \xi_{\ell,\check{k}}), \;\; \forall\, \ell \in \mathscr{S}, \tag{5}$$

where the neighbors set $\mathscr{N}_\ell$ is composed by nodes with direct communication link to node i and $w_{\ell i}$ is the weight of the link between nodes ℓ and i. Here, $\check{k}$ is the discrete time for a sampling time very close to zero. Since the graph is undirected, $w_{\ell i} = w_{i \ell}$. If the communication graph $\mathscr{G}$ is connected, and the weight of links are symmetrical, then the dynamics in (5) converge to $\boldsymbol{\xi}^\star \in \mathbb{R}^n$, where $\xi_\ell^\star = \sum_{\ell \in \mathscr{S}} \xi_{\ell,0}/n$, for all $\ell \in \mathscr{S}$ [32]. Equivalently,

$$n\xi_\ell^\star = \sum_{\ell \in \mathscr{S}} P_{\ell,\tilde{k}+1}, \quad \text{forall } \ell \in \mathscr{S},$$

Accordingly, each node in graph $\mathscr{G}$ offers data for calculating $\sum_{\ell=1}^{n} P_{\ell,\tilde{k}+1}$ and updating the Lagrange multiplier in a distributed manner. According to Olfati-Saber et al. [33] and Hendrickx et al. [34], if the out-degree of every node in the graph is equal to its in-degree and if the graph is connected, the system is average-preserving and achieves convergence. Although consensus reaches asymptotic stability when time tends to infinity, the estimation error in this application is negligible and can be fixed by local droop controllers of conventional power plants. Moreover, if the application demands more accuracy, then the aforementioned negligible error could be reduced by using acceleration techniques, e.g., Bregman-based algorithms as in [35].

3. Economic dispatch alternatives

Centralized and distributed methods for the optimal power allocation among generators are characterized by the control architectures depicted in Fig. 1. In this architecture, Fig. 1(a) presents the general scheme for the centralized MPC. Layer (L1) shows the physical layer with the n generators. On the other hand, layer (L2) solves the optimization problem in (7). Moreover, Fig. 1(b) presents the general scheme for the distributed MPC. Layer (L1) presents the physical layer with the n generators. In the second layer (L2), the optimization problem in (10) is solved, i.e., (11a) is executed. Notice that, algorithm in (11b) requires the centralized information associated to the coupled constraint. Then, layer (L3) computes, in a distributed fashion, the sum appearing in (11b).

3.1. Traditional dynamic power dispatch

In practice, power system operators minimize system operation costs in a multi-interval period by considering prevailing constraints on load, supply, generator capacity, and ramping rates [36], as shown below:

$$\underset{P_{\ell,k}}{\text{minimize}} \;\; \sum_{\ell=1}^{n} C_\ell(P_{\ell,k}) \tag{6a}$$

subject to

$$\sum_{\ell=1}^{n} P_{\ell,k} = Q_k, \tag{6b}$$

$$P_\ell^{\min} \leqslant P_{\ell,k} \leqslant P_\ell^{\max}, \tag{6c}$$

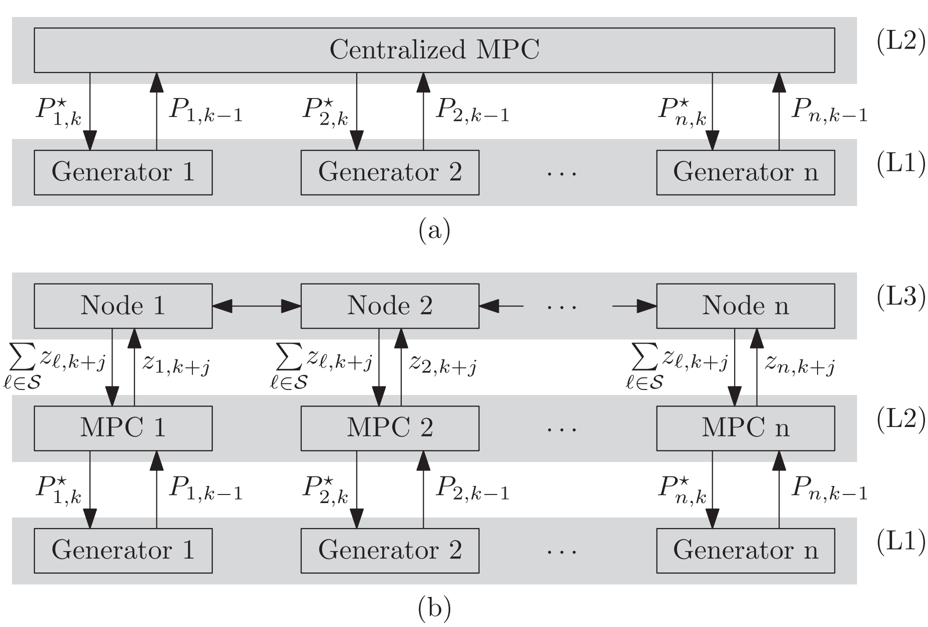

Fig. 1. Control schemes for both centralized and distributed configuration. (a) Scheme for n generators corresponding to dynamic and centralized MPC-based dispatch composed of two layers: (L1) physical layer, and (L2) control layer. (b) DDMPC scheme for n generators composed of three layers: (L1) physical layer, (L2) control layer, and (L3) consensus layer.

$$\Delta P_{\ell}^{\min} \leqslant \Delta P_{\ell,k} \leqslant \Delta P_{\ell}^{\max}. \tag{6d}$$

The optimization problem (6) is solved at every time instant $k = 1, \ldots, T$, with the consideration of generators' ramping capabilities. The balance constraint (6b) must be considered for all $k \in [1, T] \cap \mathbb{Z}_{\geqslant 0}$, whereas constraints (6c) and (6d) representing generators' physical characteristics are necessary for all $\ell \in \mathscr{S}$, $k \in [1, T] \cap \mathbb{Z}_{\geqslant 0}$. Note that if the optimization problem (6) does not consider generators' ramping capabilities (6d), it turns into a static economic dispatch problem that is independent at each time instant. However, a dispatch plan is not practically implementable if the temporal correlation of generators' power outputs, as constrained by their physical characteristics, is ignored. Even though the dynamic power dispatch respects all physical charactersitics, it might not be economic due to the fact that total costs over the operation horizon are not optimized holistically. This issue can be avoided if forecasted data representing future loading conditions in the subsequent time intervals is considered in the optimization problem (6). There have been some methods such as dynamic programming, MPC, and scenario decomposition, taking advantage of forecasted information in order to find optimal solutions at present through the perception of future conditions.

Traditional approaches for economic dispatch commonly find the optimal solution for a single interval in an off-line fashion. However, with the presence of more disturbances in the system operation due to the stochastic nature of renewable resources, off-line open-loop methods have lost efficiency and accuracy. One alternative is to implement stochastic approaches for coping with uncertainties in the system operation, but most stochastic approaches (e.g., scenario decomposition) still determine the optimal solution in an off-line fashion since an on-line feedback policy is very difficult or impossible to implement (e.g., dynamic programming), especially in the presence of inter-temporal constraints. On the other hand, MPC methods solve an open-loop finite-horizon control problem in real time for the current state of the system. Once new measurements and forecast information of the system operating condition are available, a new open-loop finite-horizon optimization problem with updated initial conditions is solved. In particular, forecast information of stochastic variables helps operators to find the optimal solution in the current state. Since MPC considers the impact of future conditions in the present operation, constraints can be included in the optimization problem more flexibly. Hence, MPC is known as an on-line closed-loop method that is capable of mitigating the risk of variability and uncertainty, and its response to large disturbances can be further improved by incorporating stochastic methods.

3.2. Centralized model predictive control

A centralized MPC approach can obtain the optimal dispatch solution as the centralized controller has information of every agent for maximizing the global benefit, e.g., minimizing total operation costs. In this case, the optimization model is formulated as a convex optimization problem:we will

$$\underset{P_{\ell,k+j|k}}{\text{minimize}} \sum_{\ell=1}^{n} \sum_{j=0}^{H_p} C(P_{\ell,k+j|k}), \tag{7a}$$

subject to

$$\sum_{\ell=1}^{n} P_{\ell,k+j|k} = Q_{k+j|k}, \tag{7b}$$

$$P_{\ell,k+j}^{\min} \leqslant P_{\ell,k+j|k} \leqslant P_{\ell,k+j}^{\max}, \tag{7c}$$

$$\Delta P_{\ell,k+j}^{\min} \leqslant \Delta P_{\ell,k+j|k} \leqslant \Delta P_{\ell,k+j}^{\max}. \tag{7d}$$

The MPC controller computes an optimal control sequence denoted by $\hat{\boldsymbol{P}}_k^{\star}$. Only the first control input from the optimal sequence is applied to the system. The balance constraint (7b) must be satisfied for all $j \in [0, H_p] \cap \mathbb{Z}_{\geqslant 0}$, and (7c) and (7d) are required for all $\ell \in \mathscr{S}$, $j \in [0, H_p] \cap \mathbb{Z}_{\geqslant 0}$.

Assumption 1. The optimization problem in (7) is feasible for all time k.

The Lagrangian function associated with the optimization problem (7) is

$$\begin{aligned} L(\boldsymbol{P}, \Lambda, \boldsymbol{\Psi}) &= \sum_{\ell=1}^{n} \sum_{j=0}^{H_p} C(P_{\ell,k+j|k}) - \lambda_{k+j}\left(\sum_{\ell=1}^{n} P_{\ell,k+j|k} - Q_{k+j|k}\right) + \psi_{\ell,k+j}^{1} \\ &(P_{\ell,k+j}^{\min} - P_{\ell,k+j|k}) + \psi_{\ell,k+j}^{2}(P_{\ell,k+j|k} - P_{\ell,k+j}^{\max}) + \psi_{\ell,k+j}^{3} \\ &(\Delta P_{\ell,k+j}^{\min} - \Delta P_{\ell,k+j|k}) + \psi_{\ell,k+j}^{4}(\Delta P_{\ell,k+j|k} - \Delta P_{\ell,k+j}^{\max}), \end{aligned} \tag{8}$$

where λ_{k+j} is the Lagrange multiplier of the coupled equality constraint (7b), $\psi_{\ell,k+j}^{1}$ and $\psi_{\ell,k+j}^{2}$ are Lagrange multipliers of constraints (7c), and $\psi_{\ell,k+j}^{3}$ and $\psi_{\ell,k+j}^{4}$ are Lagrange multipliers of constraints (7d). The corresponding Karush-Kuhn-Tucker conditions are given by

$$\begin{aligned} &\nabla_{P_{\ell,k+j|k}} L(\boldsymbol{P}^{\star}, \Lambda^{\star}, \boldsymbol{\Psi}^{\star}) \\ &= \frac{\partial C(P_{\ell,k+j|k}^{\star})}{\partial P_{\ell,k+j|k}} - \lambda_{k+j}^{\star} - \psi_{\ell,k+j}^{1,\star} + \psi_{\ell,k+j}^{2,\star} - \psi_{\ell,k+j}^{3,\star} + \psi_{\ell,k+j}^{4,\star} = 0, \end{aligned} \tag{9a}$$

$$Q_{k+j|k} = \sum_{\ell=1}^{n} P_{\ell,k+j|k}^{\star}, \tag{9b}$$

$$0 \leqslant \psi_{\ell,k+j}^{1\star}, \psi_{\ell,k+j}^{2\star}, \psi_{\ell,k+j}^{3\star}, \psi_{\ell,k+j}^{4\star}, \tag{9c}$$

$$0 = \psi_{\ell,k+j}^{1\star}(P_{\ell,k+j}^{\min} - P_{\ell,k+j|k}^{\star}), \tag{9d}$$

$$0 = \psi_{\ell,k+j}^{2\star}(P_{\ell,k+j|k}^{\star} - P_{\ell,k+j}^{\max}), \tag{9e}$$

$$0 = \psi_{\ell,k+j}^{3\star}(\Delta P_{\ell,k+j}^{\min} - \Delta P_{\ell,k+j|k}^{\star}), \tag{9f}$$

$$0 = \psi_{\ell,k+j}^{4\star}(\Delta P_{\ell,k+j|k}^{\star} - \Delta P_{\ell,k+j}^{\max}). \tag{9g}$$

Here, constraints (9b)–(9g) must hold for all $\ell \in \mathscr{S}$, $j \in [0, H_p] \cap \mathbb{Z}_{\geqslant 0}$. Fig. 1(a) shows the control scheme corresponding to the centralized model predictive control (CMPC).

A CMPC might not be manageable in a large-scale system due to the curse of dimensionality resulting from the huge number of decision variables in a multi-interval period. For example, an MPC with prediction horizon H_p and n generators has $n(H_p + 1)$ decision variables, which is intractable in large power systems, even in a deterministic optimization framework. In an uncertain environment, scenario decomposition for instance, the MPC with $n(H_p + 1)$ decision variables must be solved for every scenario. The number of scenarios depends on the number of stochastic variables (e.g., renewable generators), i.e., the greater the number of renewable generators, the greater the amount of scenarios. Therefore, the problem complexity increases with the amount of decision variables and scenarios. The distributed method proposed in this paper would be able to solve such a high-dimensionality problem.

3.3. Dual decomposition-based distributed MPC

In addition to the benefits of having a smaller communication network and less dependence on a centralized controller, the amount of decision variables and scenarios significantly decrease in each distributed problem. Since the optimal output is found locally in a DDMPC, there are $H_p + 1$ decision variables and stochastic scenarios are defined by considering the local data, i.e., without considering uncertainty from other generators. However, maximization of global benefit and fulfillment of coupled constraints are challenging in a

DDMPC. The proposed DDMPC achieves both objectives. First, global benefit is maximized in DDMPC since its objective function is derived as the dual problem of costs minimization in CMPC through KKT conditions. Second, the coupled constraint associated to the system-wide energy balance is achieved by finding its Lagrange multiplier through a consensus algorithm.

The optimization problem (7) is solved in a distributed manner by applying dual decomposition and consensus in order to deal with the coupled constraint (9b). We assume that all generators $\ell \in \mathscr{S}$ know the forecasted system load at time instant $k \in \mathbb{Z}_{\geqslant 0}$, i.e., $Q_{k+j|k}$, for all $j \in [0, H_p] \cap \mathbb{Z}_{\geqslant 0}$ is known. Note that this assumption is reasonablea single generator knows the forecasted load, and then broadcasts the information to all generators in a distributed manner based on a consensus algorithm [32]. Consider the distributed MPC controller for each generator $\ell \in \mathscr{S}$ whose optimization problem is given by

$$\underset{P_{\ell,k+j|k}}{\text{minimize}} J_\ell(P_{\ell,k+j|k}, \boldsymbol{\lambda}_k) = \sum_{j=0}^{H_p} \left\| \frac{\partial C(P_{\ell,k+j|k})}{\partial P_{\ell,k+j|k}} - \lambda_{k+j} - \psi^1_{\ell,k+j} + \psi^2_{\ell,k+j} - \psi^3_{\ell,k+j} + \psi^4_{\ell,k+j} \right\|^2, \tag{10a}$$

subject to

$$P^{\min}_{\ell,k+j} \leqslant P_{\ell,k+j|k} \leqslant P^{\max}_{\ell,k+j}, \tag{10b}$$

$$\Delta P^{\min}_{\ell,k+j} \leqslant \Delta P_{\ell,k+j|k} \leqslant \Delta P^{\max}_{\ell,k+j} \tag{10c}$$

$$0 \leqslant \psi^1_{\ell,k+j}, \psi^2_{\ell,k+j}, \psi^3_{\ell,k+j}, \psi^4_{\ell,k+j}, \tag{10d}$$

$$0 = \psi^1_{\ell,k+j}(P^{\min}_{\ell,k+j} - P_{\ell,k+j|k}), \tag{10e}$$

$$0 = \psi^2_{\ell,k+j}(P_{\ell,k+j|k} - P^{\max}_{\ell,k+j}), \tag{10f}$$

$$0 = \psi^3_{\ell,k+j}(\Delta P^{\min}_{\ell,k+j} - \Delta P_{\ell,k+j|k}), \tag{10g}$$

$$0 = \psi^4_{\ell,k+j}(\Delta P_{\ell,k+j|k} - \Delta P^{\max}_{\ell,k+j}), \tag{10h}$$

where $\widehat{P}_{\ell,k} = (P_{\ell,k|k}, \ldots, P_{\ell,k+H_p|k})$ is the sequence of control inputs for generator $\ell \in \mathscr{S}$, and $\boldsymbol{\lambda}_k = [\lambda_k \ \ \ldots \ \ \lambda_{k+H_p}]^\top \in \mathbb{R}^{H_p+1}$. The constraints (10b)–(10h) must be satisfied for all $j \in [0, H_p] \cap \mathbb{Z}_{\geqslant 0}$. The Lagrange multipliers $\boldsymbol{\lambda}_k = \boldsymbol{\varepsilon}^\star$, for $j \in [0, H_p] \cap \mathbb{Z}_{\geqslant 0}$ are computed according to the dual decomposition algorithm. Let $\boldsymbol{z}_\ell = [P^\star_{\ell,k|k} \ \ P^\star_{\ell,k+1|k} \ \ \ldots \ \ P^\star_{\ell,k+H_p|k}]^\top$ be a vector of auxiliar variables defined as $\boldsymbol{z}_\ell = \operatorname{argmin}_{P_{\ell,k+j|k}} \sum_{j=0}^{H_p} J_\ell(P_{\ell,k+j|k}, \boldsymbol{\lambda}_k)$, where $\boldsymbol{z}_\ell \in \mathbb{R}^{H_p+1}$. In addition, we define the matrix $\boldsymbol{Z} = [\boldsymbol{z}_1 \ \ \ldots \ \ \boldsymbol{z}_n] \in \mathbb{R}^{H_p+1\times n}$. Then, the dual decomposition algorithm at the time instant k, is computed as

$$\boldsymbol{z}_{\ell,\tilde{k}+1} = \arg\min_{P_{\ell,k+j|k}} \sum_{j=1}^{H_p} J_\ell(P_{\ell,k+j|k}, \boldsymbol{\varepsilon}_{\tilde{k}}), \quad \forall\, \ell \in \mathscr{S}, \tag{11a}$$

$$\boldsymbol{\varepsilon}_{\tilde{k}+1} = \boldsymbol{\varepsilon}_{\tilde{k}} + \alpha(\boldsymbol{Z}_{\tilde{k}+1}\mathbb{1}_n - \boldsymbol{q}_k), \tag{11b}$$

where $\boldsymbol{\varepsilon}_{\tilde{k}} = [\varepsilon_{0,\tilde{k}} \ \ \ldots \ \ \varepsilon_{H_p,\tilde{k}}]^\top \in \mathbb{R}^{H_p+1}$, $\boldsymbol{Z}_{\tilde{k}+1} = [\boldsymbol{z}_{1,\tilde{k}+1} \ \ \ldots \ \ \boldsymbol{z}_{n,\tilde{k}+1}] \in \mathbb{R}^{H_p+1\times n}$, $\boldsymbol{q}_k = [Q_{k|k} \ \ \ldots \ \ Q_{k+H_p|k}]^\top \in \mathbb{R}^{H_p+1}$, $\alpha \in \mathbb{R}_{\geqslant 0}$ is a constant value, and $\boldsymbol{Z}_{\tilde{k}+1}\mathbb{1}_n$, in (11b) is computed in a distributed manner by using the average consensus algorithm for all $j \in [0, H_p] \cap \mathbb{Z}_{\geqslant 0}$. The vector $\boldsymbol{\varepsilon}^\star$ corresponds to the convergence values of the iterative Eq. (11b). Note that to solve the optimization problem (10), information of $\boldsymbol{\lambda}_k$ is necessary. To calculate $\boldsymbol{\lambda}_k$ by applying (11b), output from generators must be calculated. Thereby, the only information that is being shared with neighbors to solve the economic dispatch problem is the power output.

In summary, the centralized MPC shown in (7) is addressed in a distributed manner by solving the local MPC problem presented in (10) which applies the updated Lagrange multiplier. The updated multiplier is associated to the equality constraint (9b), and uses the average consensus algorithm for its calculation. The DDMPC iterative process of each generator is depicted in Fig. 2. Note that each generator calculates independently (11a) and uses consensus with its neighbors to find $Z_{\tilde{k}+1}$. Thus, the optimization problem (11a) of each generator can be calculated in parallel, and coordinated with the other generators to apply the consensus algorithm. The consensus process is terminated when either the limit of iterations is achieved or the updated value of the Lagrange

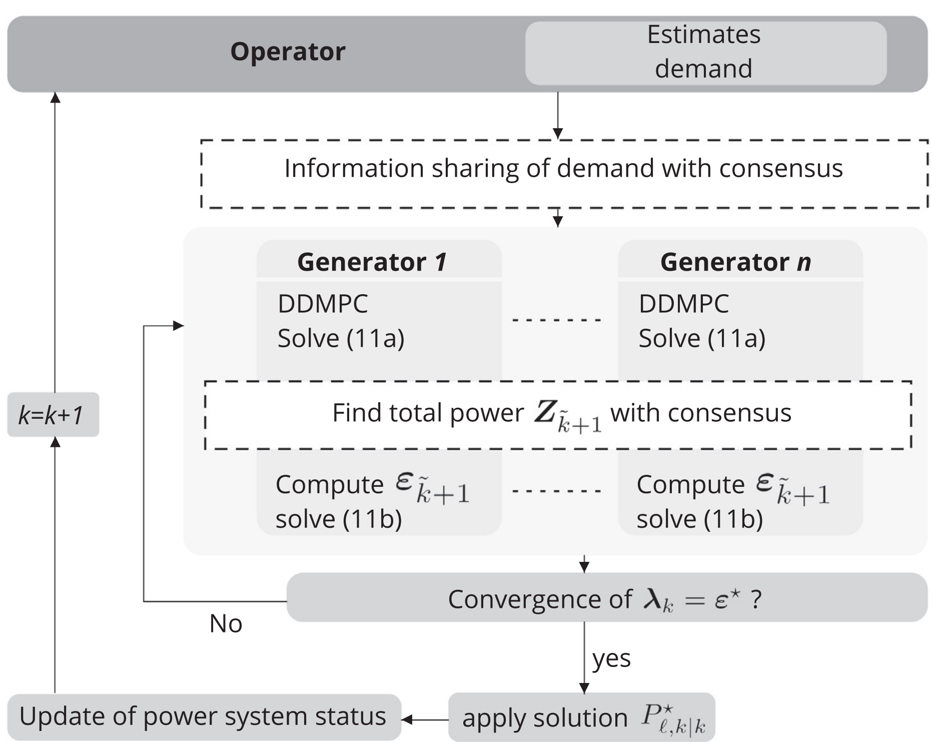

Fig. 2. Flow chart of the power system operation with DDMPC.

multiplier remains the same for a certain number of iterations. Finally, since the optimization problem stated in (7) is convex, in general there will be no optimality gap in (10).

4. Case studies and results

This section provides the results of case studies to show the benefits of using a DDMPC approach in comparison with other alternatives to perform economic dispatch. Since case studies have hourly information, $\Delta_t = 1$ hour.

4.1. Comparison of DDMPC and alternative methods

The performance of the proposed DDMPC is compared with those obtained by implementing a dynamic power dispatch strategy [36] and the DYMONDS approach [14]. We have compared our method with DYMONDS as it is one of the most promising methods for solving the economic dispatch problem with distributed and predictive features. In order to properly simulate the DYMONDS, we have included a ramp-rate constraint in *Problem 1A* of [14] to the initial condition, we have varied uniformly the price vector by 5% and 40%, and we have defined supply functions when the output vector does not change in response to the price variation. Additionally, results of the centralized MPC are not shown since they are the same as those obtained with the proposed DDMPC, i.e., the distributed approach accurately emulates its centralized counterpart. The latter can be achieved because there is no optimality gap when applying dual-decomposition to the primal problem (7).

- First scenario: This scenario shows that, under certain circumstances, the traditional dynamic power dispatch is not practically implementable. In particular, the system operation will be exposed to this undesirable condition if there is no unit commitment (UC) stage prior to the economic dispatch implementation. In this scenario, the power balance could potentially be violated as ramp-rate constraints are enforced. Generators' parameters corresponding to the first scenario are presented in Table 1. Results of the traditional dynamic power dispatch approach and the DDMPC with a forecast period $H_p = 10$ (a) and Fig. 3(b), respectively. Dispatch details of DYMONDS are not presented as they are very similar to the results obtained with the dynamic approach.

Regarding the traditional dynamic power dispatch, this control strategy is not able to satisfy balance between supply and demand at time instants $k = 2, ..., 4$, and $k = 24$. Balance is not achieved because this method uploads generator 1 to its capacity so that generator 2 is the marginal unit that supplies remaining load. However, when load decreases at the next step, generators 1 and 2 are not capable of decreasing their power generation because of their ramp-rate constraints. Ramping can be adjusted by applying a UC stage prior to the economic dispatch [37], but this increases the computational burden and data requirements. As in the dynamic dispatch case, the solution of DYMONDS with 5% variation is not feasible at time instants $k = 2, ..., 4$, but is feasible at $k = 24$, and the solution of DYMONDS with 40% variation is always feasible but very expensive (total operation cost is $3416) as it can be seen in Fig. 4(a) and (b). On the other hand, the use of multi-interval information in the DDMPC provides the required balance (see Fig. 3(b)).

In the case of the MPC-based economic dispatch, the balance of supply and demand is achieved for forecast periods $H_p = 2$ and $H_p = 10$. However, the solution performance is better when additional information of load forecast (i.e., $H_p = 10$) is available since the DDMPC controller offers an optimal control sequence, which anticipates load changes. The benefit of having a very large forecast period holds as long as the load forecast is accurate, otherwise wrong information will output non-optimal results. Nevertheless, it should be taken into account that the computation burden increases with a larger forecast period because more decision variables must be computed within the control inputs sequence. The effects of forecast period in the closed-loop performance is observed in Fig. 4(a) and (b), where the total operation cost of the DDMPC controller with $H_p = 2$ (i.e., $2412) is higher than the DDMPC cost with $H_p = 10$ (i.e., $2350). The obtained incremental cost is for a single day, which will increase as additional days are considered. Operation costs can be reduced as base generators (generator 1 in $k = 13, ..., 17$) can represent the load forecast and ramp-constraints more precisely. In this case, generator 1 decreases its power output so that generator 2 can produce more energy at peak load periods (behavior that is not possible to obtain with other control techniques justifying the implementation of predictive strategies).

- Second scenario: This scenario shows that considering multi-interval events could reduce the power system operation costs by applying preventive solutions. Here, generator 1 does not have a ramping-rate constraint and can respond flexibly to load changes, the other parameters remain the same as in the first scenario. When the load increase is larger than the ramping rate of the marginal unit, a more expensive generator must be used, thereby increasing operational costs. However, if such situation can be anticipated, base generators decrease their output and ramp-enforced generators increase their production before load increases. This action minimizes the use of expensive generators when demand rises.

From the previous results it can be seen that the dynamic dispatch and DYMONDS with 40% variation have lower costs for some specific hours than those of the DDMPC controller with $H_p = 10$, but in general the hourly and cumulative costs of these techniques are very similar. Nevertheless, the DDMPC dispatch performs much better than the dynamic dispatch and DYMONDS for some specific system conditions (e.g., second scenario). Specifically, consider the results in Fig. 5 in which the DDMPC with $H_p = 10$ has reduced the output of generator 1 at $k = 5, ..., 7$, and $k = 12, ..., 14$. This preventive action allows generator 2 to increase its production as the system reduces the dispatch of the most expensive generator. The costs shown in Fig. 6 demonstrate hourly as well as cumulative dispatch costs. The cumulative cost shows that the DDMPC with $H_p = 10$ is better than dynamic dispatch and DYMONDS from $k = 7$. In this case, the cumulative cost difference for 24 h is about "$"190 with respect to dynamic dispatch and "$"248 with respect to DYMONDS.

In summary, closed-loop features allow the DDMPC to update the system performance by considering all available options. Thereby, the DDMPC would be a promising method compared to existing ones to address economic dispatch problems in uncertain conditions with imperfect data. In addition, the MPC-based approach offers additional options for applying the optimization-based method in conjunction with predictive models. Since MPC relies on forecast of future system conditions such as the system load and availability of renewable resources, we have assumed for simplicity that the load forecasts for calculating the MPC-based dispatch are accurate.

Table 1
Parameters of generators in the first simulation case.

Generator $\ell \in \mathscr{S}$	$a_\ell[\frac{"\$"}{MW^2}]$	$b_\ell[\frac{"\$"}{MW}]$	P_ℓ^{min} [MW]	P_ℓ^{max} [MW]	ΔP_ℓ^{min} $[\frac{MW}{\Delta_t}]$	ΔP_ℓ^{max} $[\frac{MW}{\Delta_t}]$
1	0.5	1	0	3	−0.2	0.2
2	1	10	0	6	−0.2	0.2
3	2	35	0	4	−4	4

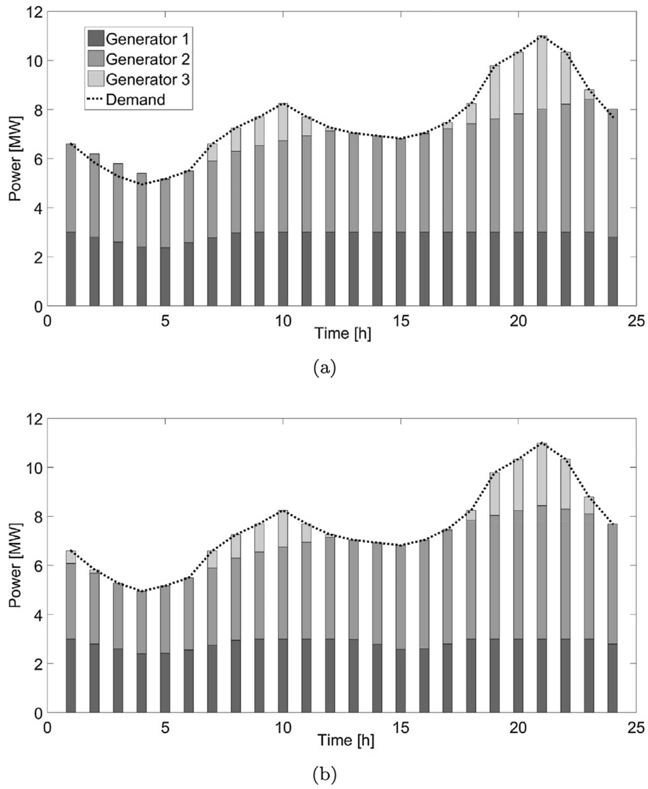

Fig. 3. Results of traditional dispatch approaches applied to the first scenario. (a) Dynamic dispatch. (b) DDMPC with $H_p = 10$.

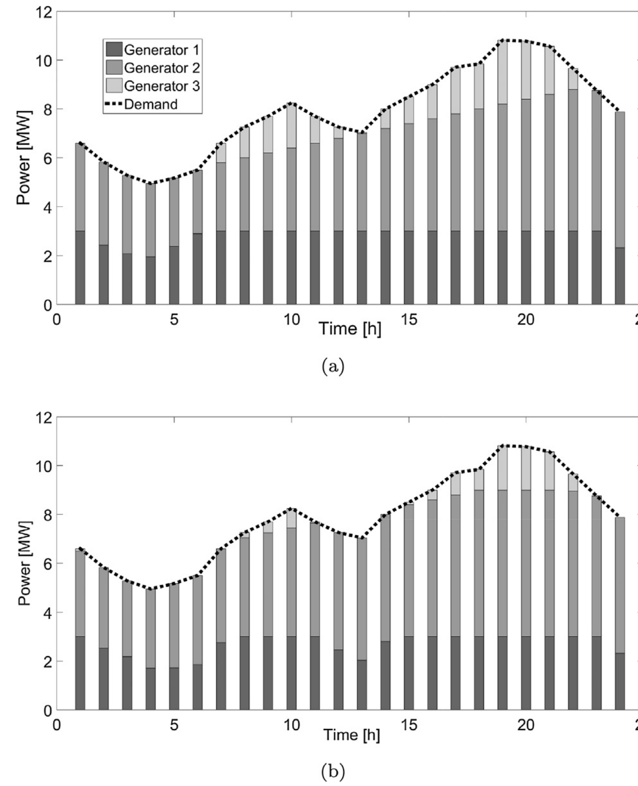

Fig. 5. Results of the second scenario. (a) Dynamic dispatch. (b) DDMPC with $H_p = 10$.

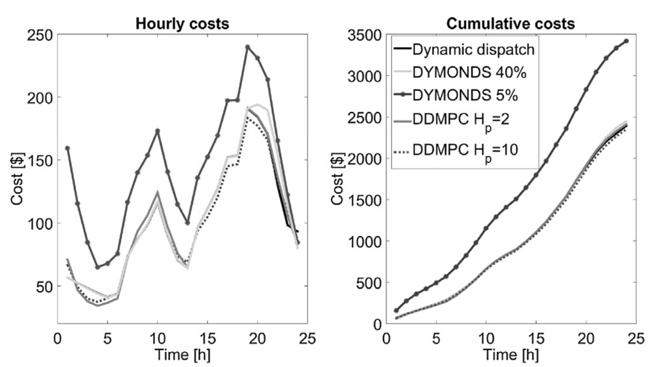

Fig. 4. Costs of the first scenario for different alternatives.

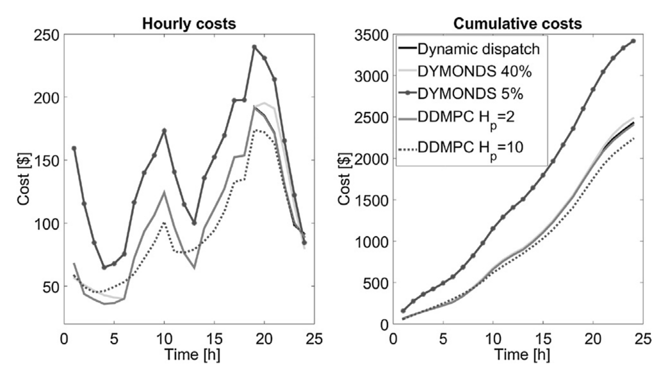

Fig. 6. Costs of the second scenario for different alternatives.

4.2. DDMPC computation performance and convergence test on a system with large penetration of renewables

In this section, we compare the behavior of DDMPC with the centralized MPC in a system with renewable energy. The comparison here only includes CMPC because it can be considered as the MPC benchmark. In addition, we have shown in the previous case that DDMPC outperforms other methods. We have modified the system presented in [14] by changing some generator parameters in order to highlight advantages of the proposed technique in the presence of renewable resources, but maintaining the peak load and the daily load profile for highlighting the MPC abilities. Then, both DDMPC and centralized MPC are simulated for different configurations to show that with more information the operator can obtain better solutions. The latter analysis is very important in the presence of renewable-based power plants. Table 2 shows the parameters of five generators with specific technical and economic characteristics. Generators 1, 2, and 3 are conventional generators, whereas generator 4 is a wind power plant, and generator 5 is based on solar photovoltaics.

Results show that the solutions obtained by DDMPC and centralized MPC are quite similar as both approaches satisfy all physical and operation constraints in a preventive framework. The convergence analysis of the DDMPC algorithm is shown in Figs. 7 and 8, while economic dispatch results of the CMPC and the proposed DDMPC are presented in Fig. 9 for different forecast periods. Since the algorithm proposed to solve the economic dispatch problem in a distributed manner is

Table 2
Parameters of generators for the second simulation case.

Generator $\ell \in \mathscr{S}$	$a_\ell[\frac{\text{"\$"}}{\text{MW}^2}]$	$b_\ell[\frac{\text{"\$"}}{\text{MW}}]$	$P_\ell^{\min}$ [MW]	$P_\ell^{\max}$ [MW]	$\Delta P_\ell^{\min}$ $[\frac{\text{MW}}{\Delta_t}]$	$\Delta P_\ell^{\max}$ $[\frac{\text{MW}}{\Delta_t}]$
1	0.5	1	0	450	−200	200
2	1	10	0	800	−100	100
3	7	35	0	1000	−30	30
4	0.1	1	0	2000	−500	500
5	0.1	0.5	0	800	−800	800

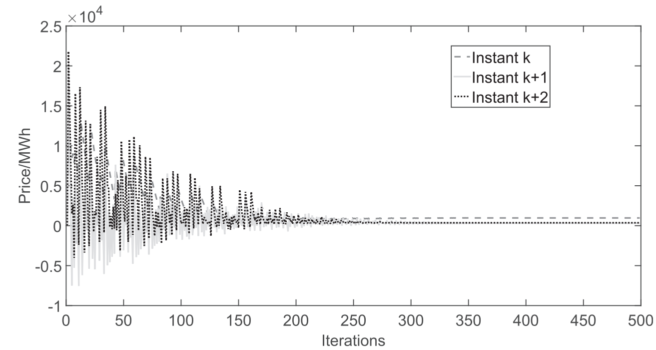

Fig. 7. Evolution of Lagrange multiplier for k = 5 and H_p = 5.

iterative, it is necessary to show that it converges to an efficient solution. Figs. 7 and 8 show the evolution of the Lagrange multiplier associated to energy balance and the evolution of power generated by each power plant at k = 5 and H_p = 5, respectively. On one hand, at the process beginning the Lagrange multiplier is very volatile, but its volatility decreases when iterations increase. Convergence of the Lagrange multiplier is achieved before 300 iterations. On the other hand, generators' output converge if the energy price is stable. In this case, the output of generators converge before 400 iterations. However, this is not always true since it depends directly on the cost functions of generators. For instance, if there is no quadratic term in the cost function, there will be several dispatch solutions for the same electricity price. This undesirable effect can be mitigated by including a very small (but different from zero) quadratic term in the cost function.

After showing convergence of the iterative DDMPC, some comparisons between CMPC and its distributed counterpart are depicted in Fig. 9 and Table 3. In Fig. 9, economic dispatch results are presented for both MPC architectures when H_p = 24. Renewable power plants are uploaded to their maximum resource availability, but there is an important difference in the behavior of conventional generators. From hour 15 renewable energy drops, especially solar, and load increases to its peak at hours 18 and 19, leading to the duck chart detailed in [38]. The duck chart may lead to power imbalances and lack of energy in ramp-constrained power systems, as it can be seen in Fig. 9 at hours 16 and 17. The lack of energy in this case is more evident in the DDMPC results. Since CMPC has an explicit constraint related to energy balance, it is more likely to achieve equilibrium of power and demand under limiting conditions such as the duck chart. On the other hand, DDMPC does not have this explicit balance constraint but an implicit signal of power deviation from load (i.e. electricity price). That is, the DDMPC

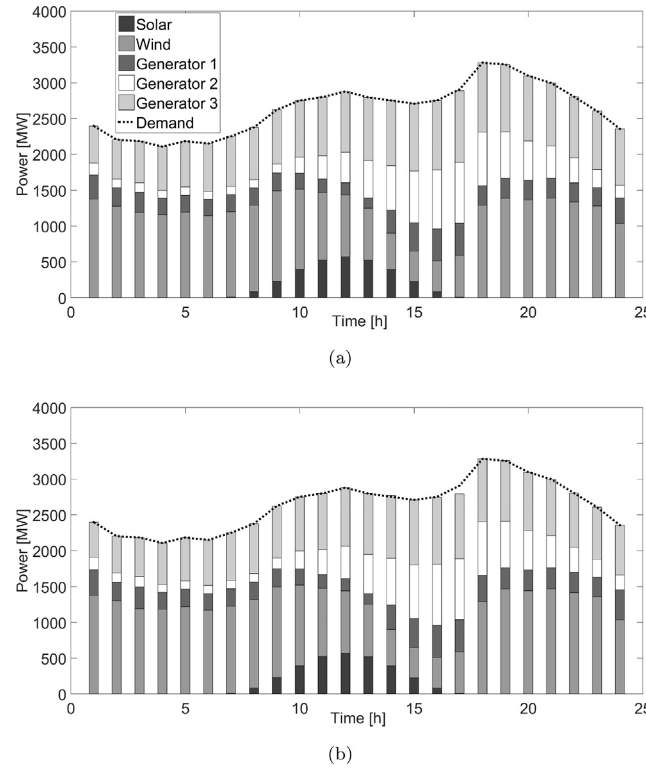

Fig. 9. Results of the second case study. Economic dispatch of (a) CMPC with H_p = 24. (b) DDMPC with H_p = 24.

may prefer load shedding if it is too expensive to comply with the balance constraint of the CMPC. In this particular case, generator 3 (the most expensive) has a higher output at early hours in CMPC than it has on DDMPC. Thus, generator 3 can be used to its maximum in order to minimize power deviations. Although this is an ideal behavior, operation costs can be potentially high as it is discussed next.

Table 3 shows unattended load and operation costs of DDMPC and CMPC when they are tested for different prediction horizons. From the results, it can be seen that as prediction horizon increases, unattended load decreases. The forecast period is an important parameter since it has a direct impact on the economic dispatch performance. However, a larger number of forecast periods also adds the computation burden. On the other hand, it can be seen that unattended load is lower in CMPC, but its costs are much higher than those of DDMPC. Gap and indexed

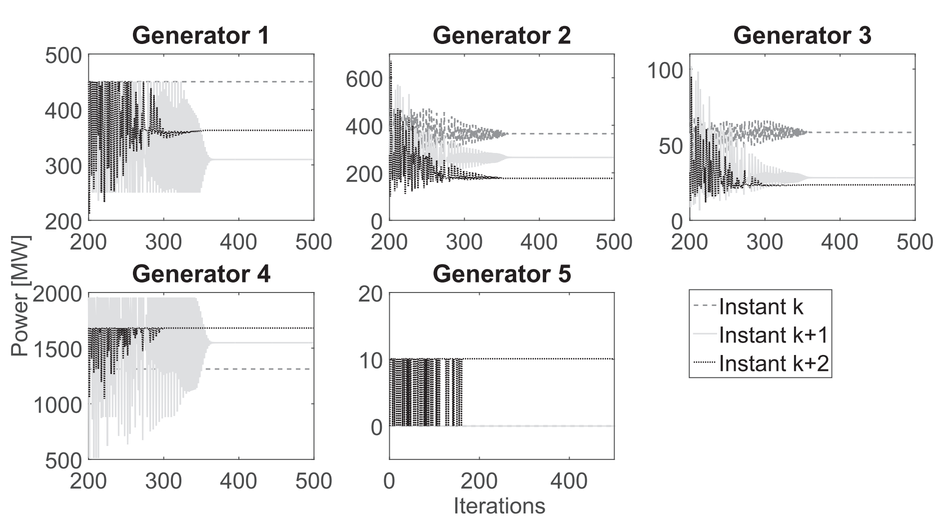

Fig. 8. Evolution of generators' power for k = 5 and H_p = 5.

Table 3
Comparison of CMPC vs DDMPC.

Prediction horizon	Unattended load [MW]		Operation cost [M$]		Gap cost	Indexed cost
	Centralized	Distributed	Centralized	Distributed	[M$/MW h]	[M$/MW h]
5	2911,00	2911,00	20,50	20,50	0,000	0,00
10	1952,50	1952,50	28,93	28,93	0,000	0,00
15	365,90	497,69	77,26	69,12	0,062	0,00096
20	19,16	131,38	119,07	104,95	0,126	0,00082
24	19,16	121,94	119,07	104,98	0,137	0,00075
48	19,16	208,61	119,07	94,61	0,129	0,00136

costs are included in Table 3 in order to highlight an important advantage of DDMPC. Gap costs represent the unitary cost of every additional MWh supplied in the CMPC, while indexed costs represent the average unitary cost if that electricity would be supplied by the most expensive generator without ramp-constraints. These two values imply that if gap costs are much higher than indexed costs (as it happens in this case), then it might be preferable to shed load. Otherwise, the electricity price will be above users' willingness to pay. DDMPC provides a strong signal regarding the need of including demand response programs (e.g. price responsive demand) in the economic dispatch problem.

Moreover, we have tested the computational complexity and scalability of DDMPC compared with a centralized MPC. Results are shown in Tables 4 and 5. Table 4 depicts the simulation time in function of the amount of generators for one time step with $H_p = 13$. Performance of the centralized MPC starts very fast, but it grows exponentially as generators increase, reaching almost two hours when 1000 power plants are considered. On the other hand, DDMPC computational time is much faster than centralized MPC as generators increase. Thus, DMPC is better for large-scale system. Computational times of DDMPC do not vary so much when a new power plant is added to the system. This result was expected as we mentioned before that one advantage of using distributed approaches that are not coupled is their scalability because of parallelization. Table 5 shows the simulation time in function of the prediction horizon for one time step with 20 generators. As in the previous case, centralized MPC starts very fast, but its computational time increases exponentially when the prediction horizon is large. Indeed, we did not calculate its behavior for $Hp = 800–2000$ because of memory capacity. On the other hand, DDMPC computational time increases as prediction horizon is larger, but it remains feasible even for very large prediction horizon. Notice that this computational analysis evaluates independently the impact of generators amount and prediction horizon. Nevertheless, if growth of both variables is considered at the same time, the need of using distributed approaches capable of running in parallel becomes more critical.

In summary, the characteristics of predictive approaches such as CMPC and DDMPC are highly valued in power systems operation, especially in those systems with a high penetration of renewable energy. As it was depicted in Fig. 9, the duck chart issues might be hedged by applying predictive strategies. In addition, DDMPC is more flexible about lack of energy and it prefers to avoid uploading very expensive generators for several periods instead of charging the users very high electricity prices. This behavior shows the need to include demand response programs in power systems operation. Additionally, we have shown the need and importance of distributed approaches in large-scale power systems by presenting scalability results. In the analyzed cases, computational times of DDMPC are lesser than $\Delta_t = 1$ hour. Thus, DDMPC is feasible for short-term applications.

5. Concluding remarks

An MPC-based distributed dispatch has been proposed to find the optimal power outputs of generators to meet a dynamic load. The proposed method achieves energy balance, while minimizing the system's operation costs in a distributed way that emulates the centralized dispatch solution by applying dual decomposition. Generators communicate with each other based on a consensus algorithm, without sharing any private information such as generation costs and capacities. The main features and contributions of the proposed DDMPC are: (i) distributed emulation of a centralized MPC; (ii) economic balance with consensus; (iii) very high granularity of agents; (iv) integration of renewables behavior in online operation of power systems; (v) assessment of renewable impact on ramp-rate limits; (vi) MPC to hedge variables volatility in large-scale power systems; and (vii) feasibility of short-term dispatch even for very large power systems.

The DDMPC performance has been successfully tested for two case studies: the first designed to show and boost the MPC benefits, and the second to verify its behavior in a case study with high penetration of renewable resources. In the first simulation case, the DDMPC is compared with the dynamic power dispatch method and DYMONDS. The obtained results show that the proposed approach is better since it can constantly anticipate changes of the system. In the second simulation case, advantages of the proposed DDMPC over CMPC are shown: (i) the communication requirement is less strict; (ii) there is less dependence on a centralized controller; (iii) the amount of decision variables decreases; (iv) there is no need of sharing private information to the system operator; and (v) the balance constraint is more flexible and potentially high electricity prices are avoided, i.e., demand response is encouraged.

As future work we plan to extend the proposed DDMPC by incorporating stochastic optimization techniques in order to tackle the challenges posed by distributed generation entities in a more flexible way. Moreover, demand response programs and possibly energy storage systems must be included within economic dispatch techniques to avoid very high electricity prices. Another topic that we are currently exploring is consideration of power flow constraints from a fully distributed approach, which is a very complex task. Finally, different approaches can be explored to enhance computational performance of the presented method in order to shorten economic dispatch intervals.

Table 4
Simulation time in function of amount of generators per each economic dispatch method and for one time step with $H_p = 13$.

# of Generators	Centralized MPC[s]	DDMPC[s]
3	0.118	4.400
10	0.207	4.540
100	2.684	4.549
200	7.208	4.630
300	13.18	6.150
400	21.69	6.780
500	31.20	7.280
750	54.88	7.212
900	1988	6.854
1000	6944	7.327

Table 5
Simulation time in function of prediction horizon per each economic dispatch method and for one time step with 20 generators.

H_p	Centralized MPC[s]	DDMPC[s]
13	0.39	5.48
24	0.75	6.41
36	1.18	7.50
72	3.56	10.56
200	14.29	29.40
300	27.12	45.47
400	44.51	65.91
500	67.64	85.81
600	1574.00	106.50
700	3843.98	131.48
800	No register	162.60
1000	No register	212.46
1200	No register	267.10
1500	No register	370.87
2000	No register	576.31

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ijepes.2019.05.044.

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