A robust MPC method for microgrid energy management based on distributed optimization

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***Abstract*— In this work we present a novel distributed MPC method for microgrid energy management based on distributed optimization. In order to cope with uncertainty in prices and renewable energy production, we adopt a robust min-max approach that optimizes at each time step the worst case scenario of the objective function. Combining the advantages of MPC and distributed optimization, the resulting algorithm is suitable for the control of large-scale microgrids in which renewable energy resources are employed. Moreover, since it is based on novel distributed optimization algorithms, the method allows the future power profiles to be computed for each microgrid component without sharing this information with the others. Simulation results for a DC microgrid system model show the effectiveness of the proposed method. The algorithm is tested in two different scenarios: in presence of uncertainties and considering perfect knowledge of the future price and power profiles.**

I. Introduction

The increasing demand for electrical energy and the necessity of power system flexibility has driven the deployment of distributed generation systems as opposed to centralized power systems. Such generation systems have three main features: they are small in size (ranging from kW to MW), they are installed close to loads and they are often renewable energy sources. The integration of a large number of distributed energy resources in the distribution power system is challenging and fuelled the development of the concept of microgrid [12] which is defined in [15] as a cluster of loads, distributed generation units and energy storage systems, operated in coordination to reliably supply electricity and connected to the power distribution grid. Typically the control of a microgrid is based on a three layers [24]: the primary level governs voltage regulation, the secondary level deals with power quality issues and the tertiary level is responsible for power management and optimization (ensure stable delivery of power to the loads while optimizing energy production and other operational goals [26]). In this paper we will focus on the tertiary layer.

The design of an energy management controller for microgrid systems is challenging for many reasons. Firstly, the use of renewables, imposes significant uncertainties which have to be handled appropriately (power production which cannot be estimated with certainty and energy price may change over the day). Secondly, dealing with large-scale microgrids generates large-scale problems involving a huge number of decision variables, requiring a great deal of computational effort. Thirdly, knowledge of the future power profiles of each microgrid agent is required to make predictions at the power distribution layer which can lead to privacy issues. The last two issues have drawn the attention of control system engineers to distributed control frameworks that allow a large-scale problem to be decomposed into a number of smaller problems which are simpler, more flexible and do not require high computational power. Moreover, providing each subsystem with a local controller implies that some of the data may not be shared with the other controllers hence maintaining some level of privacy in the network. However, many issues arise when designing distributed controllers. On the one hand, the controller may not have full knowledge of the rest of the system. On the other hand, the presence of a communication network introduces issues related to security and network imperfections. In this paper we propose a distributed energy management system based on model predictive control (MPC) and distributed optimization techniques that accommodates both uncertainty in power production and energy prices. Moreover it does not require the solution of a complex optimization problem while keeping private the future power trajectories.

The remainder of the paper is organized as follows. The review of the state of the art concludes this section. Section II presents the model of the microgrid considered in this paper. Section III presents the distributed energy management algorithm. In Section IV results of the simulations are reported. Finally in Section V there are the concluding remarks and future research directions.

Since the introduction of the microgrid concept in 2002, many energy management algorithms have been proposed. In particular optimization methods have been used and to maximise the financial income due to energy trading while minimizing environmental emissions and operating costs [2], [8]. In [2], the planning of the resources is provided for the current time step only hence without taking into account the future power profiles, while [8] proposes to compute the planning for the next 24 hours without considering uncertainty. In order to overcome the aforementioned limitations many methods based on MPC have been proposed. Since optimization is repeated at each time step based on real time measurements, MPC can efficiently compensate uncertainty. Centralised MPC has been proposed in [19], [17] and [9] to schedule the operation of storage devices, generators, controllable loads and the charging of electric vehicles. In

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[10] and [3] stochastic MPC algorithms have been used to cope with the uncertainty in the microgrid. However these methods are based on centralised algorithms which may not be suitable for large-scale microgrids. Moreover they are subject to single point failure and lead to potential privacy issues. In order to deal with the aforementioned issues many distributed MPC algorithms have been proposed. Methods proposed in [16] and in [4] are not fully distributed since they require a central unit to coordinate the distributed controllers. The distributed energy management problem is solved in [27] and [18] using a distributed MPC algorithm that shares the future power trajectories at each time step. Hence a large amount of data has to be communicated at each time step. In [1] an ADMM-based MPC algorithm is proposed to solve the energy management problem for large-scale power systems, however a central unit is required to coordinate the controllers. A fully distributed optimization-based MPC algorithm is proposed in [13] however the uncertainty that characterizes the microgrid operation is not considered. Moreover all the microgrid components are assumed to be connected to a common bus.

The aim of this paper is to propose a fully distributed energy management algorithm able to cope with uncertainty and suitable for meshed microgrids. More specifically, the novel contributions of the proposed method are:

- the algorithm is based on a robust MPC that exploits distributed optimization;
- the meshed microgrid topology is considered explicitly within the framework;
- the proposed algorithm is robust to faults occurring in the communication network.

In contrast to other MPC methods based on distributed optimization (such as [1]) the proposed MPC algorithm does not require any central unit for coordination of the agents. Hence, similarly to [13], the MPC algorithm is fully distributed. However it considers uncertainty in power generation and is suitable for meshed microgrid topologies. Moreover, through the use of novel distributed optimization algorithms reviewed in [14], the proposed algorithm does not require the exchange of future power trajectories among the components and is robust to faults in the communication network (assuming that the communication graph remains connected).

II. Microgrid model

The components of the microgrid can be renewable generators, loads and storage systems. Moreover, each microgrid is connected at one or more points with the utility grid. In the following the model of each component of the microgrid will be described.

A. Generators

Distributed renewable generators produce the power that is fed into the grid. The amount of power P_{r_i} that a generator i can inject in the microgrid is limited by the maximum power that can be produced at time t:

$$0 \leq P_{r_i}(t) \leq P_{r_i}^A(t) \tag{1}$$

The power that is fed into the microgrid is sold to the other microgrid components that pay a price p_r assumed constant. Hence, the generator agent will try to maximise the amount of power to sell to the other microgrid components. Since renewable generators are stochastic by nature, we rely on predictions of the maximum and minimum power produced at each time, that is, we consider that the actual value of produced power at time t is bounded by a known maximum and minimum value:

$$P_{r_i}^A(t) = \frac{P_{r_i}^M(t) + P_{r_i}^m(t)}{2} + w_{r_i}(t)\frac{P_{r_i}^M(t) - P_{r_i}^m(t)}{2} \tag{2}$$

where $w_{r_i}(t) \in [-1; 1]$ is a modeling parameter, $P_{r_i}^M$ and $P_{r_i}^m$ are the predicted bounds of power production.

B. Loads

Loads are characterized by their maximum and minimum power demand. In particular, we assume that each load i draws an amount of power P_{c_i} from the grid limited by a maximum and a minimum demand value:

$$d_i^m(t) \leq P_{c_i}(t) \leq d_i^M(t) \tag{3}$$

and the demand change is limited by a maximum demand rate:

$$|P_{c_i}(t+1) - P_{c_i}(t)| \leq r_{c_i} \tag{4}$$

Each load will try to maximise the power that it will draw from the grid based on its utility function $u_i(t)$ [21]. In other words, the utility function $u_i(t)$ is the weight associated with the objective function of load i.

C. Storage systems

The charge of the storage system i is modeled as:

$$s_i(t+1) = s_i(t) + \mu T_s P_{s_i}(t) \tag{5}$$

where μ is the energy conversion efficiency, T_s is the sample time of the MPC and $P_{s_i}(t)$ is the storage power (charging when $P_{s_i}(t) \geq 0$ and vice versa). Each storage has a maximum and minimum capacity (s_i^M and s_i^m):

$$s_i^m \leq s_i(t) \leq s_i^M \tag{6}$$

and maximum charging/discharging power:

$$|P_{s_i}(t)| \leq P_{s_i}^M \tag{7}$$

The objectives of a storage system in a microgrid are the peak shaving/valley filling capability [23], operating the microgrid in island mode [26] and ensuring that enough energy is stored in the grid during events such as faults [20].

D. Utility grid connection

The amount of energy that a microgrid can exchange with the utility grid through each connection i is limited:

$$|P_{g_i}(t)| \leq P_{g_i}^M \tag{8}$$

Each agent in charge of the connection to the main grid will try to minimize the amount of power that is exchanged with the main grid depending on the energy price $p_g(t)$ which is a stochastic variable. Assuming we know the predictions of the maximum and minimum electricity price, the actual electricity price at time t is expressed as in [11]:

$$p_g(t) = \frac{p_g^M(t) + p_g^m(t)}{2} + w_g(t)\frac{p_g^M(t) - p_g^m(t)}{2} \quad (9)$$

where $w_g(t) \in [-1;1]$ is a modeling parameter, p_g^M and p_g^m are the maximum and minimum bounds of electricity price.

E. Interconnection of the components

Each microgrid component is connected to a bus and buses are connected through lines. The first constraint is given by energy conservation, that is, the amount of power injected in the microgrid buses has to be equal to the amount of power drawn from the buses:

$$\sum_{i=1}^{N_B} P_{B_i}(t) = 0 \quad (10)$$

where N_B is the number of buses and P_{B_i} is the power injection in the bus i. It is assumed that the outgoing power is positive and the incoming power is negative (e.g. the power supplied to loads is positive whereas the power injected by a renewable generators is negative). The relation between the power flowing in the N_L lines and in the N_B buses in the microgrid is given by the DC power flow equation [22]:

$$\mathbf{P}_L = \mathbf{b}\mathbf{A}_B^L\mathbf{B}^{-1}\mathbf{P}_B \quad (11)$$

where:

- $\mathbf{P}_L \in \mathbb{R}^{N_L}$ is the vector obtained stacking the power that flows in each line;
- $\mathbf{b} \in \mathbb{R}^{N_L \times N_L}$ is a diagonal matrix in which each element $b(i,i)$ is the susceptance of line i;
- $\mathbf{A}_B^L \in \mathbb{R}^{N_L \times N_B}$ is the adjacency matrix in which each element $A_B^L(i,j) \in \{0, 1, -1\}$ respectively if the line i and the bus j are not connected, line i starts at bus j and line i ends at bus j;
- $\mathbf{B} \in \mathbb{R}^{N_B \times N_B}$ is the admittance matrix;
- $\mathbf{P}_B \in \mathbb{R}^{N_B}$ is the vector obtained by stacking all the bus power injections P_{B_i}.

This relation can be used to calculate the line flows given the power injected in each bus. Each line flow is limited:

$$|P_{L_i}(t)| \leq P_{L_i}^M \quad (12)$$

III. Distributed energy management system

The goal of the energy management system is to compute the optimal power profile of each component to optimize the microgrid operation. Each local controller will solve its own MPC problem communicating only with its neighbours.

A. Communication network

The communication network allows the agents to communicate with each other and solve the distributed optimization problem. Such algorithm (that will be presented in the next paragraph) requires to exchange the dual variables of the optimization problem at each time step. The communication network is modeled as an undirected graph $G(\mathcal{V}, \mathcal{E})$ where $\mathcal{V}$ is the set of nodes and $\mathcal{E}$ is the set of edges. We assume that each microgrid component (generator, load, storage and connection to the utility grid) is provided with a local controller (a.k.a agent) with communication and computation capabilities. Hence, if the total number of components is N, the cardinality of the set of nodes is $|\mathcal{V}| = N$. The matrix $A \in \mathbb{R}^{N \times N}$ denotes the adjacency matrix of the graph ($a_{i,j} = 1$ if component i can communicate with component j, $a_{i,j} = 0$ otherwise). In the remainder of the paper the neighbours of component i will denote all the nodes that can communicate with it.

B. Constrained-coupled distributed optimization

The distributed energy management MPC problem is formulated as a constrained-coupled optimization problem:

$$\min_{\{\mathbf{x}_1,\dots\mathbf{x}_N\}} \quad \sum_{i=1}^{N} f_i(\mathbf{x}_i) \quad (13a)$$

$$\text{s.t.} \quad \mathbf{x}_i \in X_i \quad (13b)$$

$$\sum_{i=1}^{N} \mathbf{g}_i(\mathbf{x}_i) \leq 0 \quad (13c)$$

in which $\mathbf{x}_i$, f_i, X_i are respectively the local decision variable (the future power profiles in this case study), the local objective function and the local constraint set of component i. The coupling constraint (13c) is used to model the interconnections of the components. This optimization problem is solved using the distributed dual subgradient algorithm presented in [6] which allows the primal solution of each agent to converge to the set of optimizers of the centralized problem without communicating the estimate of the decision variable $\mathbf{x}_i$ (hence without sharing any sensitive information). In other words, agents can cooperatively solve problem (13a)-(13c) knowing only their local variables ($\mathbf{x}_i$, f_i, X_i and $\mathbf{g}_i$) and exchanging only dual variables. Moreover, this algorithm does not require the solution of a centralised problem, differently to [13], or a long tuning procedure.

C. Local MPC problems

In this paragraph the local MPC problem formulated for each component will be described (equations (13a)-(13b)). The interconnections among the components (equations (10) and (12)) are the coupling constraint (13c) of the constrained-coupled problem. The local MPC problem of the component i of the microgrid can be written as a min-max MPC problem:

$$\min_{\{P_i(t)\dots P_i(t+T-1)\}} \quad \max_{w_i} \sum_{\tau=t}^{t+T-1} J_i(\tau) \quad (14a)$$

$$\text{s.t.} \quad s_i(\tau+1) = h_i(s_i(\tau), P_i(\tau)) \quad (14b)$$

$$P_i^m(\tau) \leq P_i(\tau) \leq P_i^M(\tau) \quad (14c)$$

$$|P_i(\tau+1) - P_i(\tau)| \leq r \quad (14d)$$

$$s_i^m \leq s_i(\tau) \leq s_i^M \quad (14e)$$

$$w_i \in \Omega_i \quad (14f)$$

where T is the MPC prediction horizon, h_i models the dynamics of component i, $P_i(t)$ is the power flow of component

i (its decision variable), w_i is a disturbance variable, $J_i(t)$ is the objective function of component i, $s_i(t)$ is the state of the component i, $P_i^m(t)$ and $P_i^M(t)$ are the minimum and maximum power flows of component i, r is the maximum power rate of component i, s_i^m and s_i^M are the state limits of component i and Ω_i is a bounded set. In the following, as commonly done in literature [25], we will assume that each objective function J_i is a convex function of the decision variables $\{P_i(t)\dots P_i(t+T-1)\}$, hence can be expressed as a quadratic form:

$$\sum_{\tau=t}^{t+T-1} J_i(\tau) = \left(\mathbf{P}_i - \bar{\mathbf{P}}_i\right)^T \mathbf{\Lambda} \left(\mathbf{P}_i - \bar{\mathbf{P}}_i\right) \tag{15}$$

where $\mathbf{P}_i$ is obtained stacking the decision variables $\{P_i(t)\dots P_i(t+T-1)\}$, $\bar{\mathbf{P}}_i$ is the set point and $\mathbf{\Lambda}$ is a diagonal matrix of weights (energy prices or utility functions). A tailored MPC problem for each component can be obtained from (14a)-(14f) using models given in Section II.

D. Distributed optimization-based MPC

Since the MPC problem (14a)-(14f) does not have the coupling among the microgrid components it is not enough to solve this problem for each component. Hence, in order to obtain a formulation like (13a)-(13c), the coupling constraints have to be added. The resulting optimization problem is (13a)-(13c) in which the vector of decision variables $\mathbf{x}_i$ is the future power profile of each component $\{P_i(t)\dots P_i(t+T-1)\}$, the objective function $f_i(\mathbf{x}_i)$ is (14a), the set X_i represents the constraints (14b)-(14f) and the coupling constraint (13c) is (10) and (12).

The algorithm proposed in [6] solves this distributed optimization problem exchanging only the dual variables of the optimization problem with the neighbours. The steps that each agent has to do at each time step are the following:

1) Set up a local optimization problem taking into account:
   - the future behaviour of stochastic variables (if any);
   - the current state of the microgrid (if the component is dynamical);
2) apply the distributed dual subgradient algorithm of [6];
3) apply the first optimal input of the computed sequence and discard the others.

IV. Simulation results

In this section an example of the application of the proposed distributed microgrid energy management approach is given. We will consider the microgrid in Figure 1 in which:

- S denotes the connection with the utility grid (agent 1);
- C_i denotes the consumer i (agents 2, 3 and 4);
- W denotes a wind generator (the renewable component, agent 5);
- ST denotes the storage system (agent 6);
- B_i denotes the buses ($N_B = 6$)
- L_i denotes the lines ($N_L = 6$)

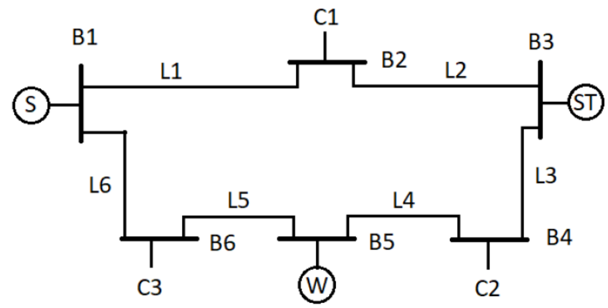

Fig. 1. 6-bus microgrid

Table I reports the main data used for the simulations and Figure 2 shows the utility function u_i for each load and the electricity price profile (p_g). Since in this setting there are not any specific objectives for the storage system (like providing energy during faults or be able to operate the grid in island mode) its objective function is set to zero. The distributed optimization problem is solved at each time step through the distributed dual subgradient method setting the number of iterations to 3000. For this simulation 10 out of 15 total communication links are active (the corresponding entries of the adjacency matrix A are set to 1). In fact this distributed optimization algorithm allows the solution to be computed even if some agents can communicate only with some of the others. Hence this algorithm is intrinsically robust to faults happening in communication links (assuming the communication graph remains connected). Simulations have been implemented using the DISROPT Python package presented in [7]. In the simulations, the power flows have

Variable	Value	Variable	Value
T	10	s_M	100 MW h
T_s	1 h	s_m	20 MW h
P_L^M	460 MW	μ	0.9
r_{c_1}	6 MW h^{-1}	P_s^M	30 MW
r_{c_2}	90 MW h^{-1}	P_g^M	200 MW
r_{c_3}	110 MW h^{-1}	p_r	20 $/MWh

TABLE I

Main simulation data

been scheduled for 24 hours of operation of the microgrid. Figure 3 and Table II present the results for two different distributed energy management methods, the prescient MPC (P-MPC, as called in [5]) and the robust min-max MPC (R-MPC). In the first case the value of the disturbance variables (w_r and w_g) is assumed known to the controller over the entire prediction horizon whereas in the second case the scheme relies on the worst case scenario of the objective function. In both cases the power demand of the loads are met, i.e. the power supplied to the loads is within the maximum and minimum power demand throughout the simulation time. The power supplied from the distribution grid is always negative, which means that energy has to be bought from the distribution grid. The amount of power that

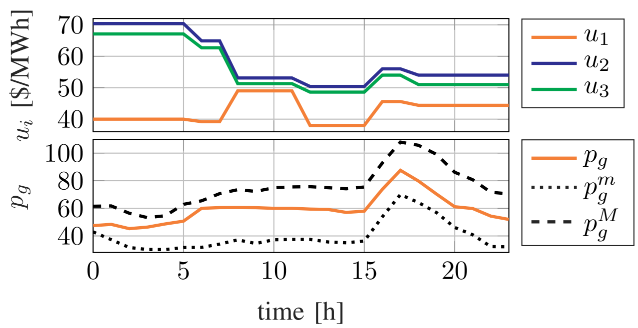

Fig. 2. Utility function (u_i) for each load and electricity price (p_g) with its limits (p_g^m and p_g^M)

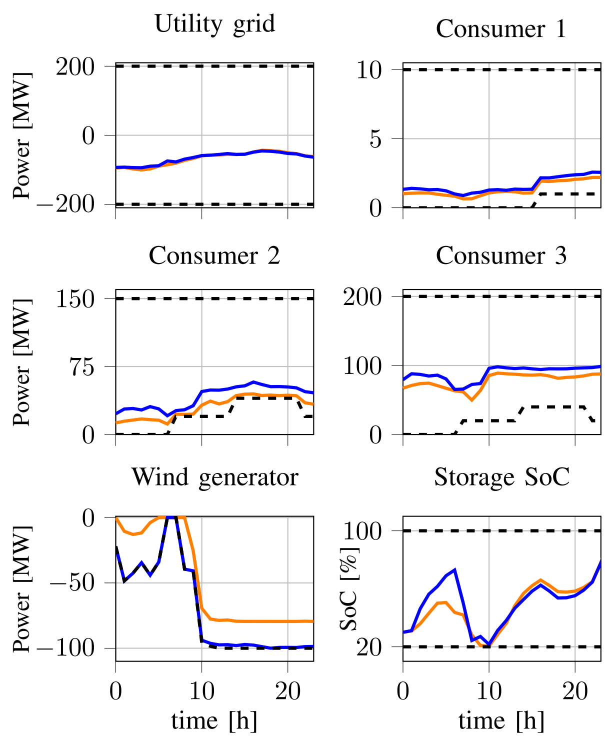

Fig. 3. P-MPC (blue) and R-MPC (orange) results: power profiles and SoC (solid) and their limits (dashed)

is supplied from the wind generator changes significantly in the two simulation cases. While in the P-MPC case the wind generator is always able to inject into the grid all the power that it can produce, in the second case it has to schedule its power profile relying on the the worst case scenario, that is, the minimum power production. The state of charge profiles are similar in the two simulation scenarios, in both cases the storage is used to store energy when wind production is high (time span 12 h to 22 h) and supply it to the loads when it is low (time span 5 h to 10 h). Table II reports some numerical results of the P-MPC and the R-MPC. The following three indices for each simulation are reported:

$$E_c = \sum_{i=1}^{3} \sum_{t=0}^{23} T_s P_{c_i} \tag{16}$$

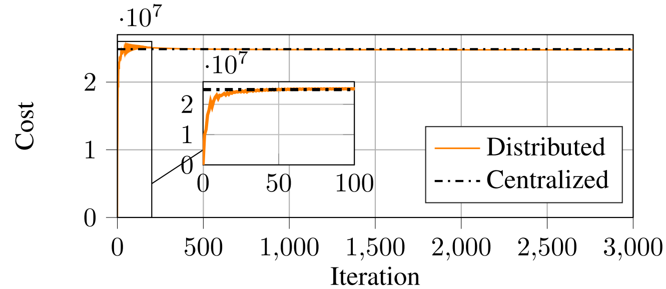

Fig. 4. Convergence of the distributed cost to the centralised cost in the R-MPC scenario

	P-MPC	R-MPC
E_c [MWh]	3158	2624
E_g [MWh]	-1592	-1626
E_r [MWh]	-1678	-1163

TABLE II

TOTAL ENERGY SUPPLIED TO LOADS (E_c), COMING FROM THE UTILITY GRID (E_g) AND SUPPLIED BY THE WIND GENERATOR (E_r)

$$E_g = \sum_{t=0}^{23} T_s P_g \tag{17}$$

$$E_r = \sum_{t=0}^{23} T_s P_r \tag{18}$$

which are respectively the total amount of energy supplied to loads, the total energy coming from the utility grid and the energy supplied from the wind generator. Since the amount of power bought from the utility grid is similar in the two cases it is clear that it is more convenient to supply less power to loads instead of buying it from the grid.

Finally, the employed distributed dual subgradient algorithm guarantees that primal variables converge to the set of optimizers of the centralized primal problem. Figure 4 (referred to the first simulation step of the R-MPC) shows the convergence of the cost of the distributed algorithm to the centralized one over the 3000 algorithm iterations.

V. Conclusion

In this paper we presented a fully distributed energy management algorithm for microgrid systems based on MPC and distributed optimization. In order to deal with uncertainty in both the power production and electricity prices we propose a robust min-max MPC algorithm. Moreover the meshed network topology has been considered in the optimization problem. The algorithm has been tested in two different scenarios. In the first we assume perfect knowledge of the disturbance variables whereas in the second they are assumed to be unknown and bounded. Simulation results show that the algorithm is suitable for energy management purposes and, thanks to the specific employed algorithm, is robust to faults in the communication network and keeps the future power trajectories private. In terms of future work, we aim to extend the capabilities of this algorithm to take into account possible faults in the microgrid components or attacks in the communication system, extensive simulation analysis will be provided.

References

[1] Philipp Braun et al. "Hierarchical distributed ADMM for predictive control with applications in power networks". In: *IFAC Journal of Systems and Control* 3 (2018), pp. 10–22.

[2] CM Colson and MH Nehrir. "A review of challenges to real-time power management of microgrids". In: *2009 IEEE Power & Energy Society General Meeting*. IEEE. 2009, pp. 1–8.

[3] Stefano Raimondi Cominesi et al. "A two-layer stochastic model predictive control scheme for microgrids". In: *IEEE Transactions on Control Systems Technology* 26.1 (2017), pp. 1–13.

[4] Alireza Dehghani-Pilehvarani, Achilleas Markou, Luca Ferrarini, et al. "A hierarchical distributed predictive control approach for microgrids energy management". In: *Sustainable Cities and Society* 48 (2019), p. 101536.

[5] Stefano Di Cairano et al. "Stochastic MPC with learning for driver-predictive vehicle control and its application to HEV energy management". In: *IEEE Transactions on Control Systems Technology* 22.3 (2013), pp. 1018–1031.

[6] Alessandro Falsone et al. "Dual decomposition for multi-agent distributed optimization with coupling constraints". In: *Automatica* 84 (2017), pp. 149–158.

[7] Francesco Farina et al. "Disropt: a python framework for distributed optimization". In: *arXiv preprint arXiv:1911.02410* (2019).

[8] W Gu, Z Wu, and X Yuan. "Microgrid economic optimal operation of the combined heat and power system with renewable energy". In: *Ieee pes General Meeting*. IEEE. 2010, pp. 1–6.

[9] Yi Guo et al. "Two-stage economic operation of microgrid-like electric vehicle parking deck". In: *IEEE Transactions on Smart Grid* 7.3 (2015), pp. 1703–1712.

[10] Christian A Hans et al. "Scenario-based model predictive operation control of islanded microgrids". In: *2015 54th IEEE conference on decision and control (CDC)*. IEEE. 2015, pp. 3272–3277.

[11] Clemens Kiebler et al. "Reserve Balancing in a Microgrid System for Safety Analysis". In: *IFAC-PapersOnLine* –.– (2020), pp. –.

[12] Robert H Lasseter. "Microgrids". In: *2002 IEEE Power Engineering Society Winter Meeting. Conference Proceedings (Cat. No. 02CH37309)*. Vol. 1. IEEE. 2002, pp. 305–308.

[13] Ivano Notarnicola and Giuseppe Notarstefano. "Constraint-coupled distributed optimization: a relaxation and duality approach". In: *IEEE Transactions on Control of Network Systems* (2019).

[14] Giuseppe Notarstefano, Ivano Notarnicola, and Andrea Camisa. "Distributed optimization for smart cyber-physical networks". In: *arXiv preprint arXiv:1906.10760* (2019).

[15] Daniel E Olivares et al. "Trends in microgrid control". In: *IEEE Transactions on smart grid* 5.4 (2014), pp. 1905–1919.

[16] Alessandra Parisio and Salvador Pacheco Gutierrez. "Distributed model predictive control for building demand-side management". In: *2018 European Control Conference (ECC)*. IEEE. 2018, pp. 2549–2554.

[17] Alessandra Parisio, Evangelos Rikos, and Luigi Glielmo. "A model predictive control approach to microgrid operation optimization". In: *IEEE Transactions on Control Systems Technology* 22.5 (2014), pp. 1813–1827.

[18] Alessandra Parisio et al. "Cooperative MPC-based energy management for networked microgrids". In: *IEEE Transactions on Smart Grid* 8.6 (2017), pp. 3066–3074.

[19] Ionela Prodan and Enrico Zio. "A model predictive control framework for reliable microgrid energy management". In: *International Journal of Electrical Power & Energy Systems* 61 (2014), pp. 399–409.

[20] Ionela Prodan, Enrico Zio, and Florin Stoican. "Fault tolerant predictive control design for reliable microgrid energy management under uncertainties". In: *Energy* 91 (2015), pp. 20–34.

[21] Morteza Rahimiyan, Luis Baringo, and Antonio J Conejo. "Energy management of a cluster of interconnected price-responsive demands". In: *IEEE Transactions on Power Systems* 29.2 (2013), pp. 645–655.

[22] Hossein Seifi and Mohammad Sadegh Sepasian. *Electric power system planning: issues, algorithms and solutions*. Springer Science & Business Media, 2011.

[23] Moslem Uddin et al. "A review on peak load shaving strategies". In: *Renewable and Sustainable Energy Reviews* 82 (2018), pp. 3323–3332.

[24] Shahid Ullah et al. "The Current State of Distributed Renewable Generation, Challenges of Interconnection and Opportunities for Energy Conversion based DC Microgrids". In: *Journal of Cleaner Production* (2020).

[25] Zaiyue Yang et al. "Economical operation of microgrid with various devices via distributed optimization". In: *IEEE Transactions on Smart Grid* 7.2 (2015), pp. 857–867.

[26] Yeliz Yoldaş et al. "Enhancing smart grid with microgrids: Challenges and opportunities". In: *Renewable and Sustainable Energy Reviews* 72 (2017), pp. 205–214.

[27] Yi Zheng, Shaoyuan Li, and Ruomu Tan. "Distributed model predictive control for on-connected microgrid power management". In: *IEEE Transactions on Control Systems Technology* 26.3 (2017), pp. 1028–1039.