Agent-based distributed hierarchical control of dc microgrid systems

Meng, Lexuan; Vasquez, Juan Carlos; Guerrero, Josep M.; Dragicevic, Tomislav

Published in:
Proceedings of Electrimacs 2014

Publication date:
2014

Document Version
Early version, also known as pre-print

AGENT-BASED DISTRIBUTED HIERARCHICAL CONTROL OF DC MICROGRID SYSTEMS

Lexuan Meng, Tomislav Dragicevic, Josep M. Guerrero, Juan C. Vasquez

Denmark Microgrids Research Programme www.microgrids.et.aau.dk
Depart. Of Energy Technology, Aalborg University, Pontoppidanstræde 101, Aalborg, Denmark.
e-mail: lme@et.aau.dk

Abstract – In order to enable distributed control and management for microgrids, this paper explores the application of information consensus and local decision-making methods formulating an agent based distributed hierarchical control system. A droop controlled paralleled DC/DC converter system is taken as a case study. The objective is to enhance the system efficiency by finding the optimal sharing ratio of load current. Virtual resistances in local control systems are taken as decision variables. Consensus algorithms are applied for global information discovery and local control systems coordination. Standard genetic algorithm is applied in each local control system in order to search for a global optimum. Hardware-in-Loop simulation results are shown to demonstrate the effectiveness of the method.

Keywords – DC microgrids, distributed hierarchical control, multi-agent systems, consensus algorithm, droop control, DC/DC converters.

1. INTRODUCTION

Hierarchical control is proposed for properly operating distributed generation, storage and loads in microgrids, three control levels are considered including primary control, secondary control and tertiary control, as shown in Fig. 1 [1], [2]. Although this control architecture is often used in AC systems, it can be adapted as well in DC microgrids, being each level described as:

- ***Primary control*** consists of voltage and current control loops as well as local load sharing methods. Droop control is most applied for communication-less power sharing among distributed generators (DGs).
- ***Secondary control*** is in charge of global voltage regulation of the microgrid, thus restoring the voltage deviation caused by droop control or to control the power flow with other DC microgrids or distribution systems.
- ***Tertiary control*** aims at optimal operation of the microgrid, achieving automatic and intelligent energy management. Decision-making (DM) and optimization are the main tasks in this level, although energy efficiency, system level safety/stability and economic issues also can be included.

Primary control is usually implemented in local control system. Distributed communication-less power sharing can be achieved by using the droop method, which has been demonstrated in a number of research works [1].

In contrast, secondary control requires information collection and global reference sharing. Although conventional secondary control is centralized, it can be realized in a decentralized fashion by utilizing communication technology and information sharing strategy [1].

In case of tertiary control, optimization and decision-making functions require accurate and reliable global information. Also a strong supervision and coordination of the whole system is needed, so that this control level is mostly located at the microgrid central controller. However, in order to increase the system redundancy and expandability, the tertiary control level could be conceived in a decentralized way as well [3].

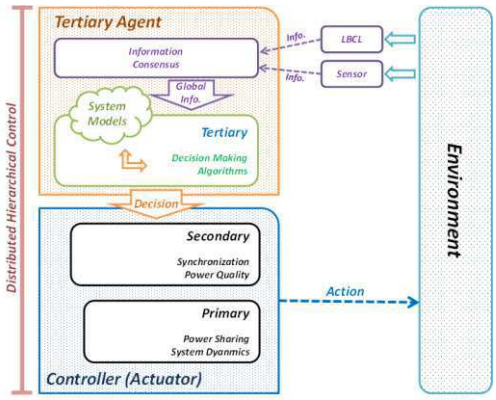
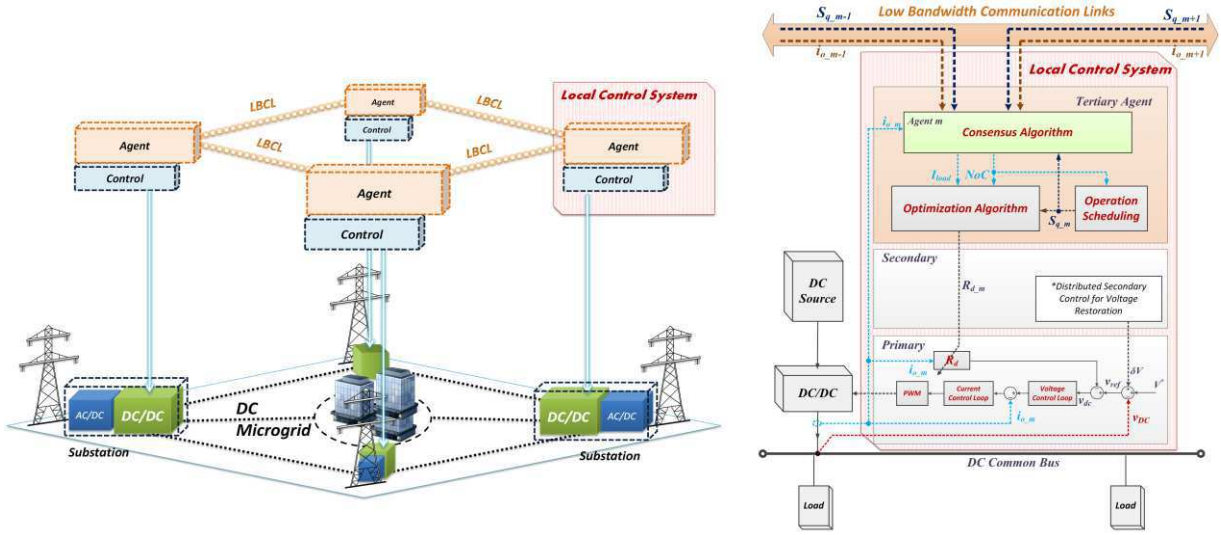


Fig. 1. Agent-based distributed hierarchical control.

I.S.B.N. 978-84-616-9961-2 –



(a) DC microgrid and distributed hierarchical control system (b) Local control system

Fig. 2. Study DC microgrid and the control system.

One way to do this is to deploy a local decision-making. If each one unit can get proper information from the others, having common objectives and knowing how its decision will influence the system, the wise and optimal action can be made locally. These three critical issues actually denote the challenges for distributed information sharing, decision-making procedure and system modelling. The combination of which formulates a distributed tertiary agent layer as shown in Fig. 1, also named multi-agent system [4], [5]. Each agent perceives its environment through low bandwidth communication links (LBCL) and sensors. Consensus algorithms can be applied to facilitate the distributed global information discovery, based on which the tertiary decision making procedure can perform optimization or scheduling functions. System models are established for evaluating the environment reaction and assisting the DM process. Finally, proper actions are taken to change the behaviour of the environment. Controller layer works as actuators between agent and environment.

Based on this scheme, conventional centralized DM functions can be performed in a distributed way so as to fit into the new paradigm of distributed generation and consumption in microgrids. This paper is organized as follows. A distributed paralleling DC/DC converter system is taken as a microgrid case study in this paper, which is introduced in Section 2. Section 3 presents the basics and application of consensus algorithm in the microgrid. Also the proper weights setting for consensus algorithm is also presented so as to obtain desirable convergence. Hardware-in-loop implementation and results are shown in Section 4 to demonstrate the effectiveness of the method. Section 5 gives the conclusion.

2. Study Case

2.1. Distributed Energy Conversion in a DC Microgrid

A case study system is shown in Fig. 2 (a). There are four distributed substations that transfer power from external grids to a DC microgrid (common bus voltage 48V). They are implemented in different places. Two-stage conversion system is implemented in each substation. The AC/DC converters are non-controllable diode rectifiers. The power conversion can be controlled by regulating DC/DC converter stage. The local control system consists of primary and secondary controller layer, and tertiary agent layer. LBCL are established between neighbouring substations for coordination and information sharing. Each converter can convert maximum 20A current (1kW).

The detailed local control system is shown in Fig. 2 (b). The inner voltage and current control loops as well as the droop control loop are integrated in primary level. Droop control loop is implemented here as a virtual resistance (VR, of value R_d) feedback before the voltage control loop. In this paper, a dynamic VR shifting [6] method is applied for changing the output current of each converter to a desirable value.

Distributed secondary voltage restoration is required so as to recover the voltage deviation caused by droop control, but it is out the scope of this paper.

The tertiary agent consists of a dynamic consensus algorithm (DCA) for global information discovery and an optimization algorithm for global efficiency optimum searching. The VR values (R_d) are taken as decision variables. An operation scheduling

I.S.B.N. 978-84-616-9961-2 –

procedure is also implemented in tertiary level for coordination among distributed converters. Two information states are shared among local control systems by using consensus algorithm: the local output current (i_{om}, m=1,2,…,N_{oC}, of which N_{oC} denotes the total number of converters) and the priority number of each converter (S_{qm}=1,2,…,N_{oC}). The local output currents value is used for total load current (I_{load}) averaging, this information is necessary for the optimization process. The S_{qm} is used for knowing the total number of online converters as well as the operation priority of the local converter.

2.2. Optimization Problem Formulation

The typical efficiency curve of DC/DC converters and the basic principle of VR shifting are shown in Fig. 3 [7]. Assuming the stable input and output voltage, the efficiency of each converter is changing with their output current. The maximum efficiency is usually obtained between 1/3 load to full load conditions. Accordingly, it is not efficient that all the converters equally share the load current as opposed to the conventional static droop control especially under light load conditions.

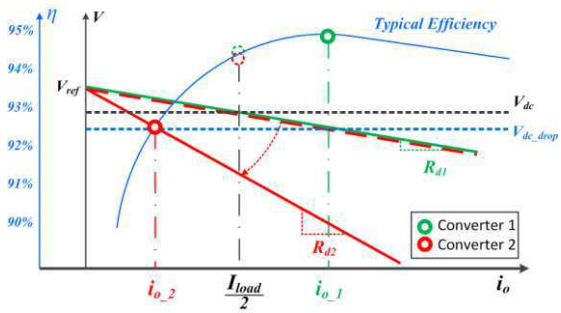


Fig. 3. Typical efficiency curve and adaptive VRs.

As droop control is implemented in each local controller, it is possible to change their VRs so as to adjust the load current sharing proportion among all the converters. The general method is outlined in Fig. 3, in which a two-converter system is analyzed. They are given the same voltage reference (V_{ref}). If fixed VRs are applied, the two converters are equally supplying the total load current (i_{o1}=i_{o2}=I_{load}/2). In light load conditions as shown in the figure, it was demonstrated in [6] that the system overall efficiency can be enhanced if the sharing proportion among converters is differentiated.

The objective of the optimization problem is to minimize the system total power losses defined as:

$$P_{TL} = \sum_{m=1}^{N} V_{DC} \cdot i_{om} \cdot \frac{1-\eta_m}{\eta_m} \qquad (1)$$

where V_{DC} is dc bus voltage, i_{om} and η_m are the output current and efficiency of the mth converter.

The decision variables are the VR values in each local control system (R_{d1},R_{d2},…,R_{dNoc}). The load current sharing proportion is changed with VR:

$$i_{o1} : i_{o2} : \ldots : i_{oN_{oC}} = \frac{1}{R_{d1}} : \frac{1}{R_{d2}} : \ldots : \frac{1}{R_{dN_{oC}}} \qquad (2)$$

The advantage of using VRs as decision variables is that by changing VR values, it will readjust the load current sharing proportion among all the converters, while the total current generated and supplied are always balanced. However, the common bus voltage and also the system level stability are affected. Distributed secondary control restores the DC bus voltage, and detailed analysis of stable VR range are presented in [6].

This optimization problem is subject to:

$$s.t.: \begin{cases} 0.25 \le \left\{ R_{d1}, R_{d2}, \ldots, R_{dN_{oC}} \right\} \le 5 \\ \left\{ i_{o1}, i_{o2}, \ldots, i_{oN_{oC}} \right\} \le I_{MAX} \end{cases} \qquad (3)$$

which states that the shifting range of VRs should be within a certain stable range and the output current of each converter is limited to I_{MAX}. Genetic algorithm (GA) is used in this paper to solve this optimization problem.

2.3. Implementation of Tertiary Agent System

The consensus algorithm provides two kinds of information: the total load current and the number of converters. Based on this knowledge, the local optimization procedure can generate a set of optimal VRs $\{R_{d1},R_{d2},\ldots,R_{dNoc}\}^{OPT}$. The local operation scheduling procedure decides which value in the optimal set should be taken for local using according to the local priority number (S_{q_m}). As in light load conditions, lower number of converters are operating which may cause fast wear&tear for the converters which are always working. Accordingly, the priority number can be shifted after a fixed cycle so as to distribute the working load among all the converters.

3. Dynamic Consensus Algorithm

3.1. Dynamic Consensus Algorithm

The general purpose of consensus algorithms [8]–[10] is to allow a set of agents to arrive to an agreement on a quantity of interest by exchanging information through communication network, while these agents are only required to communicate with

I.S.B.N. 978-84-616-9961-2 –

neighbouring agents. Each of the agents holds its own information state x_m ($m=1,2,\ldots N_{oC}$). The information state update is modelled by a difference equation in cases of discrete-time systems:

$$x_m(k+1) = x_m(k) + \sum_{n \in N_m} a_{mn} \cdot (x_n(k) - x_m(k)) \quad (4)$$

where $x_m(k)$ denotes the dynamic state of agent i at the kth iteration, and a_{mn} denotes the weight value on the communication edge between node m and n, which defines the dynamics of the information consensus. After certain number of iterations, the final consensus can be achieved as the average value of the states of all the agents:

$$\lim_{k \to \infty} x_m(k) = \frac{1}{N_{oC}} \cdot \sum_{j=1}^{N_{oC}} x_j(0) \quad (5)$$

A dynamic version of this algorithm with constant edge weights is applied in this paper which ensures the accurate averaging under dynamic states changing conditions [10]:

$$x_m(k+1) = z_m + \varepsilon \cdot \sum_{n \in N_m} \delta_{mn}(k+1) \quad (6)$$

$$\delta_{mn}(k+1) = \delta_{mn}(k) + x_n(k) - x_m(k) \quad (7)$$

where ε is the constant edge weight between any pair of agents, $\delta_{mn}(k)$ stores the cumulative difference between two agents, and $\delta_{mn}(0) = 0$. Based on (6) and (7), it is explicit that the final consensus value depends on z_m, and regardless any changes to z_m, the algorithm will converge to an appropriate average. Also, the precise consensus can also be achieved even under dynamic change of communication topology or adding/reducing number of agents.

The vector form of the consensus algorithm is:

$$X(k+1) = W \cdot X(k) = (I - \varepsilon L) \cdot X(k) \quad (8)$$

with $X(k) = [x_1(k), x_2(k), \ldots, x_{N_{oC}}(k)]^T$, W as the *weight* matrix and L as the *Laplacian matrix* of the communication network.

As the constant weight ε defines the dynamics of the algorithm, it has to be properly chosen so as to ensure the fast and stable convergence of the algorithm. It is demonstrated in [10] that the fastest convergence can be obtained when the spectral radius of matrix $W - (1/N_{oC}) \cdot \mathbf{1} \cdot \mathbf{1}^T$ is minimized. The optimal ε that offers the fastest converging speed can be calculated as:

$$\varepsilon = \frac{2}{\lambda_1(L) + \lambda_{n-1}(L)} \quad (9)$$

where $\lambda_j(\cdot)$ denotes the jth largest eigenvalue of a symmetric matrix.

In the study case microgrid, a ring shape bidirectional communication network is established in which the four local control system communicate with their neighboring substations. The *Laplacian matrix* in the study case microgrid is defined as:

$$L = \begin{bmatrix} 2 & -1 & 0 & -1 \\ -1 & 2 & -1 & 0 \\ 0 & -1 & 2 & -1 \\ -1 & 0 & -1 & 2 \end{bmatrix} \quad (10)$$

the eigenvalues of which are $[0\ 2\ 2\ 4]^T$. According to L and its eigenvalues, the optimal $\varepsilon = 1/3$.

3.2. Implementatİon of Consensus Algorİthm

The required information are total load current (I_{load}) and the total number of online converters (N_{oC}). The total load current can be obtained by each agent node by sending the output current of the local converter to neighboring units. The equilibrium of load current calculation achieved in each agent node is the average value of the total load current:

$$i_{eq} = \frac{\sum_{m=1}^{N_{oC}} i_{o\_m}}{N_{oC}} \quad (11)$$

based on which the total load current can be calculated by multiplying N_{oC} to i_{eq}.

In order to know the number of online converters, the priority number of each converter ($S_{q\_m}=1,2,\ldots,N_{oC}$) is used and sent to neighboring units. The equilibrium of the priority information can be obtained as:

$$S_{eq} = \frac{\sum_{m=1}^{N_{oC}} S_{q\_m}}{N_{oC}} = \frac{\frac{N_{oC}(N_{oC}+1)}{2}}{N_{oC}} = \frac{N_{oC}+1}{2} \quad (12)$$

based on which N_{oC} can be calculated as:

$$N_{oC} = 2S_{eq} - 1 \quad (13)$$

4. Hardware İn the Loop Results

The complete system model is shown in Fig. 4. The averaged DC/DC converter model along with its primary controller is used. In tertiary level, GA is used for optimization purposes, DCA is applied for

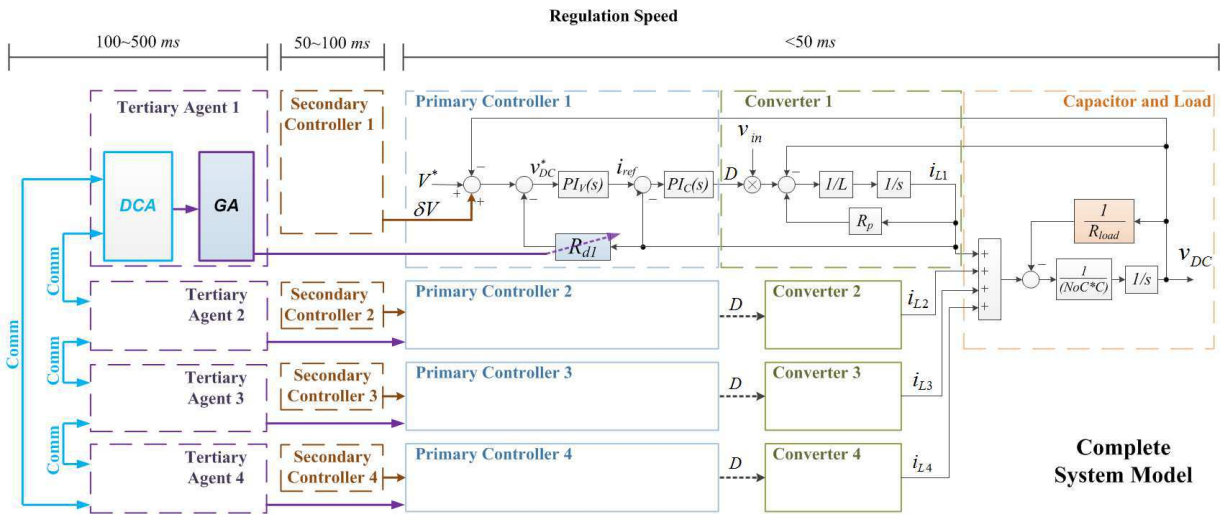


Fig. 4. Complete system model for HiL simulation.

information discovery. Communication links are built between neighboring agents. The complete model is compiled into dSPACE for HiL simulation. The results are presented in the following part.

4.1. Information Consensus

The DCA is required to provide optimization algorithm with accurate averaged state information even under dynamic states change and topology change conditions. The simulation results are shown in Fig. 5 to verify the capability of accurate and reliable information consensus by using this algorithm.

Considering the communication speed limitation, the consensus algorithm is executed every 100ms. At 0s, the initial value of the four agents are set to X_0=[1 3 5 7]^T respectively. The averaging is reached in less than 1s. At 2s, the state of agent 1 is changed from 1 to 5, the new average value is obtained as 5, which demonstrate that the algorithm is able to provide accurate average value under dynamic state change. At 4s, the communication link between agent 1 and agent 4 is disconnected. The DCA is able to assist all the agents to converge to the right value. At 7s, the state value of agent 3 is changed from 5 to 3, all the agents are able to obtain the new average value 4.5 after one communication link is broken. The simulation results demonstrate that the DCA is able to help all the agents converge to right value under dynamic state change and communication topology change.

However, under new topology, the converging speed is slower which requires local adaptive weight setting algorithm so as to always obtain the fastest convergence.

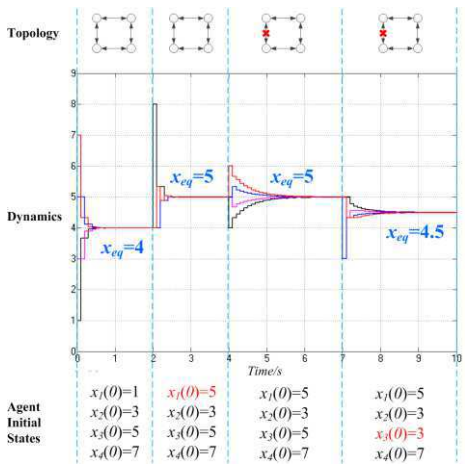


Fig. 5. Information consensus.

4.2. System Efficiency Improvement

Simulation results of the complete system model are shown in Fig. 6. A load profile is input to the system. The load consumption is changing between 500W to 2500W. Fig. 6 (b) shows that the DCA is able to help the four local agents obtain the knowledge of total load current, although some disturbance exist during the process, which is shown in Fig. 7. In Fig. 6 (c) and (d), a comparison has been made between optimized system and equivalent current sharing system, which demonstrate that the method is able to reduce the system total power loss and enhance the overall efficiency, especially under light load conditions. Fig. 6 (e) shows that nearly 10% energy loss has been saved after one load profile cycle. Fig. 6 (f) shows the current curves of the four converters. It indicates the strategy of operating the system. In light load conditions, less converters are supplying, while the others are under stand-by mode.

I.S.B.N. 978-84-616-9961-2 –

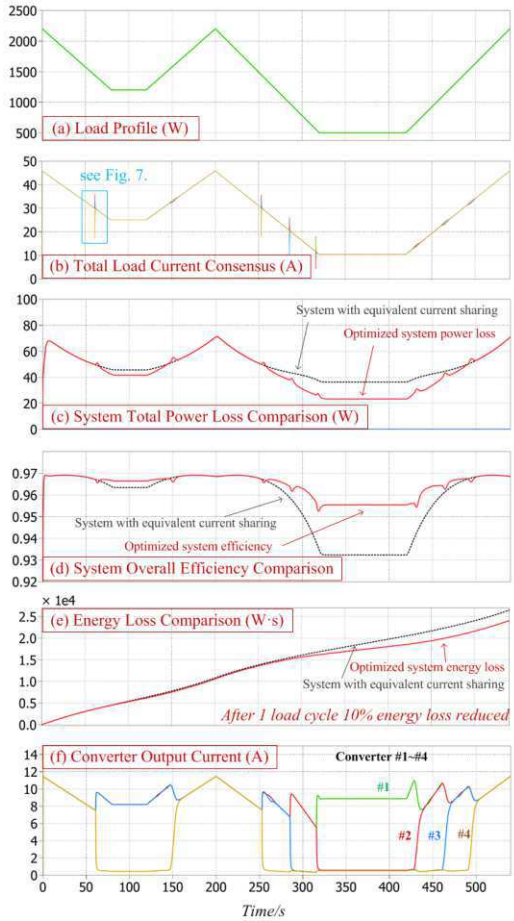


Fig. 6. Complete model simulation.

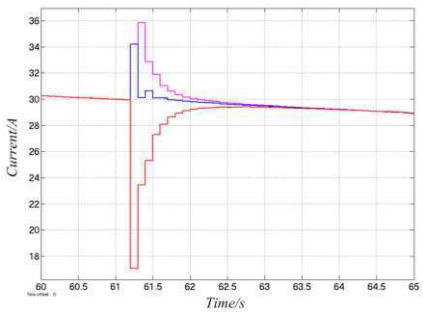


Fig. 7. Information consensus for total load current.

5. Conclusion

This paper presents a distributed hierarchical control architecture which consists of primary current sharing control based on an adaptive virtual resistance, secondary voltage restoration control and tertiary agent for global information discovery and optimization. Consensus algorithm facilitates the global information sharing as well as the performing of optimization function. The optimization along with scheduling decides the optimal number of operating converters so as to minimize the overall losses. The *HiL* simulation results are shown to demonstrate that the proposed method provides enhanced system efficiency and reduced power losses compared with non-optimized system.

References

[1] A. Bidram and A. Davoudi, "Hierarchical Structure of Microgrids Control System," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1963–1976, Dec. 2012.

[2] J. M. Guerrero, J. C. Vasquez, J. Matas, L. G. de Vicuna, and M. Castilla, "Hierarchical Control of Droop-Controlled AC and DC Microgrids—A General Approach Toward Standardization," *IEEE Trans. Ind. Electron.*, vol. 58, no. 1, pp. 158–172, Jan. 2011.

[3] T. Dragicevic, J. Guerrero, and J. C. Vasquez, "A Distributed Control Strategy for Coordination of an Autonomous LVDC Microgrid Based on Power-Line Signalling," *IEEE Trans. Ind. Electron.*, vol. PP, no. 99, pp. 1–1, 2013.

[4] F. Katiraei, R. Iravani, N. Hatziargyriou, and A. Dimeas, "Microgrid Management," *IEEE Power Energy Mag.*, pp. 54–65, 2008.

[5] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, vol. 60. 2003, pp. 269–72.

[6] L. Meng, T. Dragicevic, J. M. Guerrero, and J. C. Vasquez, "Optimization with system damping restoration for droop controlled DC-DC converters," in *2013 IEEE Energy Conversion Congress and Exposition*, 2013, pp. 65–72.

[7] P. Klimczak and S. Munk-Nielsen, "Comparative study on paralleled vs. scaled dc-dc converters in high voltage gain applications," in *2008 13th International Power Electronics and Motion Control Conference*, 2008, pp. 108–113.

[8] Y. Xu and W. Liu, "Novel Multiagent Based Load Restoration Algorithm for Microgrids," *IEEE Trans. Smart Grid*, vol. 2, pp. 140–149, 2011.

[9] R. Olfati-Saber, J. A. Fax, and R. M. Murray, "Consensus and Cooperation in Networked Multi-Agent Systems," *Proc. IEEE*, vol. 95, 2007.

[10] L. X. L. Xiao and S. Boyd, "Fast linear iterations for distributed averaging," *42nd IEEE Int. Conf. Decis. Control (IEEE Cat. No.03CH37475)*, vol. 5, 2003.

I.S.B.N. 978-84-616-9961-2 –