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Distributed control of small-scale power systems using noncooperative games ☆

Ana M. Ospina, Nicanor Quijano *

Department of Electrical and Electronics Engineering, School of Engineering, Universidad de los Andes, Bogotá, Colombia

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ABSTRACT

Distributed energy resources (DERs) coordination problems and load shedding in power systems can be modeled as a distributed resource allocation problem with physical constraints. The dynamic resource allocation problem can be approached using nonlinear methods based on population dynamics. This paper presents an optimization model to minimize the load curtailments needed to restore the equilibrium of the operating point when the system is in a fault condition (e.g., loss of generation). A mathematical model of the proposed strategy for the dispatch generation and an optimal load shedding algorithm are shown. The developed methodology minimizes the load cuts depending on the load relevance of each node of the system, and carrying out the power distribution of the generators under the new demand power condition using the replicator dynamics or the local replicator equation. This model can be used for the operation planning of electrical power systems with DERs. In order to illustrate our methodology, some simulations are performed using the IEEE 34 node test feeder in OpenDSS.

Introduction

The reliability and efficiency of electrical power systems have always been a fundamental issues of concern in network planning and operation. Therefore, a suitable planning and expansion of the power system infrastructure is required in order to incorporate new emerging forms of generation, such as the distributed energy resources (DERs).

In this context, the smart grid (SG) is envisioned to be a large-scale cyber-physical system that can improve the efficiency, reliability, and robustness of power and energy grids by integrating advanced techniques from various disciplines such as power systems, control, communications, signal processing, and networked systems. This heterogeneous nature of the smart grid motivates the adoption of advanced techniques to overcome the various technical challenges at different levels such as design, control, and implementation [1]. On the other hand, the concept of a microgrid is defined as a networked group of distributed energy sources, such as solar panels or wind turbines, located at the distribution network side, and which can provide energy to small geographical areas. Microgrids can be viewed as a small-scale power systems (SSPS). The network of microgrids is envisioned to operate both in conjunction with the grid, as well as autonomously in isolated mode [2]. In this regard, controlling the operation of the microgrids, and integrating them in the SG, introduce several technical challenges that need to be addressed so as to ensure an efficient and reliable grid operation. On that account, game theory is expected to be a key analytical tool in the design of the future smart grid, as well as large-scale cyber-physical systems. Game theory is a formal analytical and conceptual framework with a set of mathematical tools enabling the study of complex interactions among multiple independent rational players or systems [1].

The multi-agent systems (MAS) framework approach has been applied to many power engineering problems. MAS technology is now being developed for a range of applications including: energy management and electricity auction markets [3], voltage control [4], management and control for distribution grid [5–7], power systems reliability and restoration [8], etc. The main idea behind MAS is to model complex infrastructures, such as electricity networks, as a network of distributed, autonomous, and adaptive intelligent agents that are working together to achieve a global goal. One of the principal advantages of implementing MAS is their ability to learn from their interaction with the environment in order to adapt to changing operational conditions [9–11]. MAS

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* Corresponding author. Tel.: +57 1 3394949x3631.
E-mail addresses: am.ospina214@uniandes.edu.co (A.M. Ospina), nquijano@uniandes.edu.co (N. Quijano).

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are more than a systems integration method, they also provide a modeling approach. By offering a way of viewing the world, an agent system can intuitively represent a real-world situation of interacting entities, and give a way of testing how complex behaviors may emerge [12].

The grid is conventionally operated in a centralized way, where the planning of power generation is made to optimize the social welfare in the grid, and the real-time grid operation is monitored and controlled with a SCADA supervisory scheme [13]. Depending on the regulation, independent power providers can enter the electricity market and sell cheap power to the grid, and the deployment of distributed renewable energy resources are inducing the need for distributed operating system. In addition, climate change concerns, together with high oil prices and government support are driving an increase in renewable energy legislation, incentives, and commercialization.

Within the context of SG, game-theoretic tools have been used to study several applications in multi-agent systems such as congestion control in the Internet [14], security and privacy issues in wireless communications [15], mechanism design in pricing issues [16], transmission loss allocation [17], and charging methods for plugged in hybrid electric vehicles [18]. The applications of noncooperative games and learning algorithms in the SG are numerous. On the one hand, noncooperative games can be used to perform distributed demand-side management and real-time monitoring or to deploy and control microgrids [19–21]. Additionally, noncooperative games provide several frameworks ranging from classical oligopoly market game to advanced dynamic games, which enable to optimize and devise pricing strategies that adapt to the nature of the grid [1]. In [22] the authors address the problem of optimally dispatching a set of DERs without relying on a centralized decision maker. They propose a low-complexity iterative algorithm for DER optimal dispatch that relies, at each iteration, on simple computations using local information acquired through exchange of information with neighboring DERs. In [22] a wireless testbed developed for testing the performance of the algorithms is also described. On the other hand, in [23] a distributed algorithm is proposed for control and coordination of loads and DERs in distribution networks. In [24], a game-theoretic approach is used to control the decision process of individual sources and loads in small-scale and DC power systems.

In this paper, we consider a decentralized energy management scheme for the distributed generation in SSPS, and optimal load shedding in loss of generation cases. We establish a game-theoretic framework to model the generators dispatch problem in an AC power system as a MAS considering technical and economic factors. In addition, we consider a fault condition (e.g., loss of generation), where we propose an optimal load shedding based on the system physical conditions given the fault. Our work is related to [13,25,26]. In [13] a game-theoretic framework is established for modeling the strategic behavior of buses that are connected to renewable energy resources, and a study of the distributed power generation at each bus is performed. In [25], a centralized replicator dynamics approach is presented for dynamic resource allocation in the dispatch of distributed generators in a microgrid. On the other hand, the authors in [26] propose a novel distributed technique, based only on the available information of the individual subsystems named the local replicator equation (LRE), to solve the same problem. Our approach differs from these algorithms mainly in two aspects. Firstly, we show the operation of the methodology in a power system (IEEE 34 node test feeder) using OpenDSS to deal with physical operation constraints in the system. Secondly, we consider a fault condition (e.g., loss of generation) that needs the implementation of additional techniques to maintain the voltage stability in the system (e.g., load shedding). By considering a test power system and a fault condition we are able to study a more realistic approach to existing problems in SGs.

The remainder of this paper is organized as follows. In Section "Review of fundamental concepts", we briefly review some key concepts. In Section "Dispatch of distributed generators", we study the dispatch of distributed generators in microgrids while in Section "Load shedding algorithm", we discuss the load shedding algorithm. In Section "Simulation results", we present the simulation results. We present the discussion of the results in the Section "Discussion". Finally, the conclusions and future work are provided in Section "Conclusion".

Review of fundamental concepts

In this section we review two fundamental concepts relative to this paper: replicator dynamics in population game and load shedding.

Replicator dynamics in population games

The replicator dynamics equation describes how certain behavioral characteristics of a population of individuals evolve via natural selection by means of their mutual interactions and their relative fitness [27]. In this sense, the welfare that a population share of agents perceives by living in a specific habitat is measured by a fitness function that depends on the characteristics of the habitat and on the distribution of the population in the environment. The fundamental principle of these concepts is that, after an evolutionary process, the population tends to reach an equilibrium point where all individuals achieve the same fitness. In this sense, each individual attempts to maximize its payoff, which also depends on the strategies of the other individuals. By doing this, at equilibrium, a common social welfare is obtained for the total population.

Replicator dynamics with full information

To model the replicator equation, let the set of nodes $\mathcal{H} = \{1, \ldots, N\}$, be the set of pure strategies (Nhabitats), $x_i(t) \geqslant 0$ be the relative amount of individuals playing strategy i, and $x = [x_1 x_2 \ldots x_N]^\top$ be the population state. In this case, x_i is a normalized state variable, and in consequence, $x(t) \in \Delta$ for all t, where

$$\Delta = \left\{ x \in \mathbb{R}^N_+ : \sum_{i \in \mathcal{H}} x_i = 1 \right\}. \quad (1)$$

Assuming that the number of players in the population is large enough to approximate the amount of individuals playing a certain strategy as a continuous variable, the replicator equation is given by [27]

$$\dot{x}_i = x_i \left(f_i(x) - \bar{f}(x) \right), \quad \text{for all } i \in \mathcal{H}, \quad (2)$$

where $f_i : \Delta \to \mathbb{R}$ represents the fitness function that the individuals perceive in the ith habitat, and $\bar{f}(x)$ is the average fitness of the population defined as:

$$\bar{f}(x) = \sum_{j \in \mathcal{H}} x_j f_j(x). \quad (3)$$

According to this definition, the habitats whose fitness are greater than the average tend to increase their population shares, while the relative amount of individuals playing a less profitable strategy tend to decline. Moreover, the set Δ is positively invariant under Eq. (2) as a consequence of the definition of the average fitness [27,28]. Hence, if the initial population state $x(0) \in \Delta$, then all trajectories of the system remain in Δ, for all $t \geqslant 0$. The steady state of Eq. (2) is achieved when $x_i^*(f_i(x^*) - \bar{f}(x^*)) = 0$, where $x^* = [x_1^* x_2^* \ldots x_N^*]^\top \in \Delta$ is the equilibrium point. If $x_i^* > 0$, for all i, the equilibrium point satisfies the condition

$$f_i(x^*) = \bar{f}(x^*) = \bar{f}^*, \quad \text{for all } i \in \mathcal{H}, \quad (4)$$