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Fuzzy Q-Learning for multi-agent decentralized energy management in microgrids

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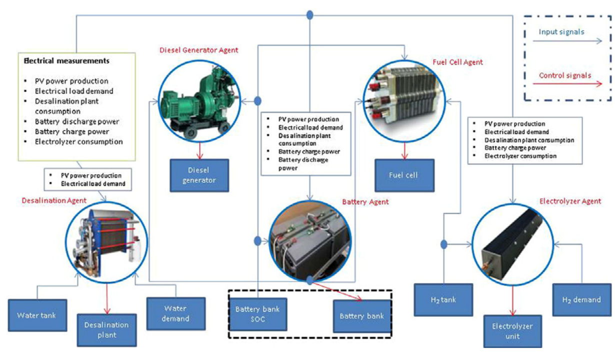
HIGHLIGHTS

- Power balancing with a fully decentralized framework.
- MAS with modified Independent Learners approach for energy management of microgrid.
- MAS and Fuzzy Q-Learning for continuous states and actions space.
- Reinforcement Learning (Q-learning) for Collaborative MAS.

GRAPHICAL ABSTRACT



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ABSTRACT

This study proposes a cooperative multi-agent system for managing the energy of a stand-alone microgrid. The multi-agent system learns to control the components of the microgrid so as this to achieve its purposes and operate effectively, by means of a distributed, collaborative reinforcement learning method in continuous actions-states space. Stand-alone microgrids present challenges regarding guaranteeing electricity supply and increasing the reliability of the system under the uncertainties introduced by the renewable power sources and the stochastic demand of the consumers. In this article we consider a microgrid that consists of power production, power consumption and power storage units: the power production group includes a Photovoltaic source, a fuel cell and a diesel generator; the power consumption group includes an electrolyzer unit, a desalination plant and a variable electrical load that represent the power consumption of a building; the power storage group includes only the Battery bank. We conjecture that a distributed multi-agent system presents specific advantages to control the microgrid components which operate in a continuous states and actions space: For this purpose we propose the use of fuzzy Q-Learning methods for agents representing microgrid components to act as independent learners, while sharing state variables to coordinate their behavior. Experimental results highlight both the effectiveness of individual agents to control system components, as well as the effectiveness of the multi-agent system to guarantee electricity supply and increase the reliability of the microgrid.

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Nomenclature

MAS	multi-agent system
FLS	Fuzzy Logic System
D_m	fuzzy set of inputs
c	output variable of fuzzy rule
w_i	firing strength of rule i
(∩)	intersection operator
a	global output/action
S_i	fuzzy sets of state variables
η	learning rate
R	reward
q	q-value of rule
AG	set of agents
T	state transition function
MDP	Markov Decision Process
f	weight function
pwt	percentage water in the tank
ed	water demand of electrolyzer (l/h)
P_L	demanded power of the variable electrical load (W)
R_{DA}	reward of desalination agent
SOC	state of charge
P_{BC}	battery charge power (W)
R_{BAT}	reward of battery agent
p_{H_2}	percentage of hydrogen in the tank
d_{H_2}	demanded hydrogen of fuel cell (m^3/h)
α_{bat}	control signal of the battery agent
P_{FC}	power produced by the fuel cell (W)
P_{DG}	power produced by the diesel generator (W)
DC	Direct Current
V	cumulative expected discounted reward
PV	photovoltaic
RL	Reinforcement Learning
$\boldsymbol{x}$	crisp input/state vector
E	output fuzzy set defined by the expert
(∪)	union operator
a_i	consequent/action of rule i
TSK	Tagaki-Sugeno-Kang
X_i	set of state variables
γ	discount factor
FIS	fuzzy inference systems
t	set of discrete time points
A	set of discrete actions
p	transition probability
Q	Q-function
ANFIS	neuro fuzzy inference system
wd	water demand (l/h)
P_{PV}	photovoltaic potential power production (W)
pbdesalination	power balance for desalination agent (W)
P_{des}	power consumption of the desalination unit (W)
pb_Battery	power balance for battery agent
P_{BD}	battery discharge power (W)
L_p	percentage of the demanded power of the dynamic electrical load
pb_Electrolyzer	power balance for electrolyzer agent (W)
R_{EA}	reward of electrolyzer agent
R_{FCA}	reward of fuel cell agent
R_{DG}	reward of fuel cell agent
MF	membership function
Π	policy
E	expectation operator

1. Introduction

1.1. Microgrids and control

For several decades, the power production is based on a central system with large scale conventional power plants and extended power transmission networks with lack in flexibility and extensibility [1]. Nowadays, the trend in power generation is changing and shifting to the distributed power generation paradigm [2]. This new model allows incorporation of new technologies with low or zero emission of gasses which do not affect the environment [3].

Microgrids are usually low voltage networks with distributed power generation units, storage devices and controllable loads [4]. They have clearly defined electrical boundaries that act as single controllable entities with respect to the grid [5]. Microgrids can operate in either grid-connected or island-mode [6]. Their ability to operate in island-mode makes them an ideal solution in remote areas, rural areas and islands [7] where the grid expansion is either impossible or cost prohibitive [8].

The ability of operating in grid-connected mode makes them an efficient economic solution in power market [9]. Thus, microgrids are exceptional infrastructure for serving the current trend of distributed power generation [10–11]. On the other hand, despite the benefits provided by the microgrid architecture there are some challenging tasks. The most challenging task is the energy management of the microgrid. In grid connected mode, in many cases, the energy management has to deal with economic problems. The schedule of the energy storage and use has to be optimal, in order to maximize the economic benefits under the dynamic prices of the electricity market.

In island mode, the main challenge is to guarantee electricity supply and maintain (or increase) reliability of the microgrid under the uncertainties which are introduced by the renewable power sources and the stochastic demand of the consumers. This becomes even more challenging when the number of renewable power sources and dynamic loads increase [12]. A centralized management and control system presents limitations, requiring distributed sources and loads to communicate their state to the central controller, while the control actions have to be broadcasted back to each unit [13–14]. In doing so, given components' possible states, the number of global system states increase exponentially to the number of components, which is also the case for the combination of components' control actions [15]. Additionally, failure of the central controller decreases the reliability of the system. The aforementioned limitations can be addressed by applying a decentralized control method. The computational load is shared among the local controllers of each system components, while the reliability of the system increases, since a failure in the local controller may not affect the whole system's performance [16]. A considerable benefit of decentralized control is that new components may be added seamlessly to the whole system, or existing components may be replaced with new ones, given that their controllers satisfy information sharing requirements for the whole system to operate successfully.

1.2. Microgrid and multi-agent system (MAS)

A multi-agent system consists of a group of agents that interact with each other and with their environment [17]. This system is ideal for solving complex problems by factoring the problem to a number of smaller and simpler ones that can be solved in more computational efficient ways than using a single-agent system. Additionally, it provides solutions that respects the autonomy of components (e.g. each component has different operating preferences, constraints, etc.). These features make multi-agent systems ideal for solving energy management problems [18].

MAS have been previously used by researchers to deal with the task