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Equilibrium-inspired multiagent optimizer with extreme transfer learning for decentralized optimal carbon-energy combined-flow of large-scale power systems

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HIGHLIGHTS

- A shared responsibility of carbon emission is introduced in decentralized OCECF.
- An equilibrium-inspired multiagent optimizer is proposed for decentralized OCECF.
- The Nash game can ensure a self-organizing optimal operation of each agent.
- The convergence rate can be dramatically accelerated by extreme transfer learning.
- The carbon emission and power loss of power network can be significantly reduced.

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ABSTRACT

This paper proposes a novel equilibrium-inspired multiagent optimizer (EMO) with extreme transfer learning for decentralized optimal carbon-energy combined-flow (OCECF) of large-scale power systems. The original large-scale power system is firstly divided into several small-scale subsystems, in which each subsystem is regarded as an agent, such that a decentralized OCECF can be achieved via a Nash game among all the agents. Then, a knowledge matrix associated with a state-action chain is presented for knowledge storing of the previous optimization tasks, which can be updated by a continuous interaction with the external environment. Furthermore, an extreme learning machine is adopted for an efficient transfer learning, such that the convergence rate of a new task can be dramatically accelerated by properly exploiting the prior knowledge of the source tasks. EMO has been thoroughly evaluated for the decentralized OCECF on IEEE 57-bus system, IEEE 300-bus system, and a practical Shenzhen power grid of southern China. Case studies and engineering application verify that EMO can effectively handle the decentralized OCECF of large-scale power systems.

1. Introduction

Since the UK Energy White Paper was published in 2003 [1], growing attentions have been paid to the low-carbon economy with the frequent occurrence of extreme weather and climate events [2]. As one of the largest CO_2 producers, electric power industry contributes more than 40% of global anthropogenic CO_2 emissions and over 24% of total greenhouse gas emissions among energy-consuming industries [3]. Therefore, the power system is encountering a crucial task of efficiently reducing the carbon emissions on both generation sides and power networks [4].

In recent years, the low-carbon power system has been extensively studied while plenty of new and advanced approaches have been proposed, including economic emission dispatch [5], low-carbon unit commitment [6], demand side response (DSR) programmes [7], carbon trading based on partially auctioning emission allowances [8], CO_2 constraint based optimal power flow (OPF) using energy storage [9], carbon capture of coal power plants based on the real-time decision support framework [10], and carbon capture and storage with bioinspired materials [11]. Moreover, most of the studies have considered the renewable energy (e.g., wind power and photovoltaics) thanks to their inherent feature of zero-carbon

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Nomenclature

Sets

W	generator set
N_L	set of branches
N_i^p	set of nodes of the pth subsystem
$N_G{}^p$	set of units of the pth subsystem
$N_C{}^p$	set of compensation equipment of the pth subsystem
$N_T{}^p$	set of transformer taps of the pth subsystem
$N_L{}^p$	set of branches of the pth subsystem
$SA_p{}^{Best}$	set of state-action pairs of the best individual of the pth subsystem
J	set of individuals

Variables

C_G	carbon emission of generation side
C_{loss}	carbon emission of grid side
C_D	carbon emission of demand side
P_{loss}	active power loss
V_i, V_j	voltage magnitude of the ith and jth node
C_{pgc}	carbon emission obligation of the power grid company
f_p	objective function of the pth subsystem
x_p	variables vector of the pth subsystem
V_d	voltage deviation index for voltage stability
P_{Gi}	active power output of the ith node
Q_{Gi}	reactive power output of the ith node
P_{Di}	active power demand of the ith node
Q_{Di}	reactive power demand of the ith node
Q_{Ci}	reactive power compensation of the ith node
T_k	transformer tap ratio
S_l	apparent power of the transmission line l
$\boldsymbol{Q^{pi}}$	knowledge matrix of the ith controllable variable of the pth agent
a_k	a selected action at the kth iteration
s_k	a state at the kth iteration
R	reward function
F_p^j	fitness function of the jth individual
$F_p{}^{Best}$	minimum fitness function of the best individual for the pth agent
$\mathbf{H}$	hidden layer output matrix
$\boldsymbol{\beta}$	output weight vector
$\mathbf{Q}_{st}$	training data
$\hat{\mathbf{Q}}_{nt}$	initial knowledge matrices of the new task
$\Delta\boldsymbol{Q}^p$	matrix 2-norms of knowledge matrices differences
q	number of inequalities violating constraints

Parameters

δ_w	carbon emission intensity of the wth generator
α_p	producer responsibility share
β_c	consumer responsibility share
μ_1, μ_2, μ_3	weight coefficients
V_i^{max}, V_i^{min}	maximum and the minimum of V_i
M	number of small-scale subsystems
α	culture learning factor
γ	discount factor
ε	exploitation rate
W	positive multiplicator
η	penalty factor

Indices

p	index of agent
k	index of iteration
j	index of individual

Abbreviations

OPF	optimal power flow
OCECF	optimal carbon-energy combined-flow
EMS	energy management system
PSO	particle swarm optimization
EMO	equilibrium-inspired multiagent optimizer
AIMS-Q(λ)	approximate ideal multi-objective solution Q(λ)
SI	swarm intelligence
GSO	group search optimizer
ABC	artificial bee colony
ELM	extreme learning machine
GA	genetic algorithm
QGA	quantum genetic algorithm
ACS	ant colony system
ALO	ant lion optimizer
TLBO	teaching-learning-based optimization
ICA	imperialist competitive algorithm

emission compared with that of thermal power. A robust environmental-economic dispatch [12] with the wind power and carbon capture plants is proposed so as to minimize the generation costs and reduce the carbon emissions. Besides, a generation planning model of a grid-connected microgrid with photovoltaic and energy storage is examined for a low carbon economy and sustainable development based on carbon trading [13].

However, these work mainly aim to minimize the total carbon emission of generation side for power generation companies, while the carbon emission of power network for power grid companies was ignored, which may not drive power grid companies for carbon emission reduction. In order to investigate the relationship between the energy consumption and the carbon emission of the power system, a carbon emission flow of power network was firstly proposed in [14]. Inspired by this, a carbon flow tracing method [15] is presented for carbon accounting and local carbon intensity assessment, respectively. Furthermore, a centralized optimal carbon-energy combined-flow (OCECF) was developed by [16] based on the carbon flow tracing method, which is a comprehensive low-carbon optimization model for power system by considering the carbon emission of power network. However, four issues are still remained challenging for the centralized OCECF according to the control center analytics [17], security and privacy [18] of smart grid, as follows:

- The complexity of centralized OCECF may grow dramatically as the scale of the power system increases, thus a relatively high computation burden or poor performance may be resulted in due to the 'curse of dimension'.
- It is usually difficult to achieve a real-time centralized OCECF because of the limit of communication capacity, as massive status information of all the electric power equipment has to be continuously transmitted to the centralized energy management systems (EMS).
- The centralized OCECF cannot satisfy the requirement of high reliability of smart grid due to the low reliability of centralized EMS.
- The centralized optimization approaches cannot resolve the centralized OCECF in practice, as the regional power grids usually belong to different owners who generally just concern their own privacy and security.

To handle the aforementioned obstacles, this paper proposes a novel decentralized OCECF by dividing the original large-scale