Applied Energy 230 (2018) 189–206

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

The impact of electric vehicle penetration and charging patterns on the management of energy hub – A multi-agent system simulation

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HIGHLIGHTS

- A multi-agent system is developed to simulate the operation of an energy hub with electric vehicles.
- Different penetration rates and various charging patterns of electric vehicle are modelled.
- A full random dispatch algorithm is integrated in smart charging strategy.
- The maximum capacity and potential of vehicle to grid is calculated.

ARTICLE INFO

Keywords:
Multi-agent system
Electric vehicle
Charging pattern
Penetration rate
Energy hub

ABSTRACT

In this paper, a multi-agent system (MAS) was developed to simulate the operation of an energy hub (EH) with different penetration rates (PRs) and various charging patterns of electric vehicle (EV). Three charging patterns, namely uncontrolled charging pattern (UCP), rapid charging pattern (RCP) and smart charging pattern (SCP), together with vehicle to grid (V2G), were simulated in the MAS. The EV penetration rates (EV-PRs), from 10% to 90% with a step of 20%, are considered in this study. Under the UCP, the peak load increases by 3.4–17.1% compared to the case without EVs, which is the reference case in this study. A main part of the increased electricity demand can be supplied by the gas turbine (GT) when the PR is lower, i.e. 71.7% under 10% PR and 37.4% under 50% PR. Under the SCP, the charging load of EVs is shifted to the valley period and thus the energy dispatch of the EH at 07:00–23:00 remain the same as that in the reference case. When V2G is considered, the electricity demand from the grid becomes the largest in all of the cases, e.g. the demand with 50% PR doubles the electricity demand in the reference case. However, the GT output decreases by 2.9–15.7% at 07:00–23:00 due to the effect of V2G. The variations in the EH's operation further raise the changes in energy cost, i.e. the electricity and cooling prices are lowered by 18.3% and 33.8% due to the availability of V2G and the heating and cooling prices increase by 3.5% and 4.3% under the UCP with the PR of 50%. Regarding the V2G capacity, near 39% of the EVs' battery capacity can be discharged via V2G. In addition, the paper also produced a V2G potential line, which is an effective tool to provide the maximum potential of the EVs for peak shaving at any specific time.

1. Introduction

In recent years, climate change and environmental pollution have continued to draw public attention to energy issues. To establish clean and reliable energy systems, novel techniques have been increasingly implemented on both the demand and supply side of energy systems [1]. The integration of advanced technologies is vital for the transition of energy systems.

On the demand side, researchers have focused on demand side management (DSM) in order to achieve load shift [2,3]. Charging of Electric Vehicles (EVs) as a new type of energy demand has been growing rapidly in recent years [4]. EVs offer opportunities for effective demand side management, utilizing their flexibility with regards to the time of charging [5,6]. Smart charging technology is a candidate solution to load shifting [7]. In the meantime, EVs can also feed power back to the grid based on the vehicle-to-grid (V2G) technology. The integration of EVs charging architecture with distributed energy sources shows considerable mobility [8]. Suitable management of EVs'

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https://doi.org/10.1016/j.apenergy.2018.08.083
Received 2 May 2018; Received in revised form 31 July 2018; Accepted 15 August 2018

Nomenclature

Abbreviation

EV	electric vehicle
DSM	demand side management
V2G	vehicle to grid
EH	energy hub
MAS	multi-agent system
PR	penetration rates
UCP	uncontrolled charging pattern
RCP	rapid charging pattern
SCP	smart charging pattern
MEDA	multi-energy demands agent
EVA	electric vehicle agent
EHA	energy hub agent
CCA	comprehensive coordination agent
SOC	state of charge
COP	coefficient of performance
NHTS	National Household Travel Survey
PDF	probability distribution functions
GT	gas turbine
AC	absorption chiller
PV	photovoltaic
GB	gas boiler
EC	electrical chiller

Variables

T	time of the day (hour)
t	duration time (hour)
D	driving distance (km)
N	number of the journeys
B	battery capacity (kWh)
P	power (kW)
E	electricity consumption (kWh)
C	cooling energy consumption (kWh)
H	heat energy consumption (kWh)
G	nature gas consumption (kWh)
p	electricity price (RMB/kWh)
h	heat energy price (RMB/kWh)
c	cooling energy price (RMB/kWh)
η	energy transfer efficiency
a	available charging time (hour)
e	charging efficiency
M	cost (RMB)
p(SOC)	probability of the event

Subscript and superscripts

max	maximum value of the variable
min	minimum value of the variable
total	joint value of the variable
n	number of the journey
t	index of time
o	original situation
d	drive situation
s	stay situation
out	outside situation
p	parking situation
B	back home situation
S	start charge
L	low level
H	high level
1n	first journey of next day
dt	energy demand at t time

charging strategy can reduce consumers' electricity cost under dynamic pricing mechanisms [9,10]. Existing studies have investigated the impacts of EVs' charging on the grid and the specific focuses of existing studies include: harmonic power ancillary service [11], overcoming voltage unbalance [12,13], integration with renewable energy sources [14,15] and net-zero buildings/houses [16,17]. However, the literature mainly took a perspective of electric engineering, while the relationship between EVs' charging patterns and the operation of distributed multi-energy systems, which were also called energy hubs (EHs), needs to be investigated.

On the supply side, EH integrates multiple types of renewable energy and traditional energy networks to meet consumers' various energy demands [18,19]. The uncertainty of energy demands, which are dependent on energy users' behavior, can influence the design, operation and performance of EHs [20]. In previous studies, EHs were managed for residential [21,22], commercial [23], public [24] or comprehensive energy use [25,26]. References [27–30] have comprehensively reviewed the energy management strategies for EHs, especially in terms of flexibility, reliability and the integrated potential of energy saving. The demand side management methods in multi-energy systems and related value analysis were overviewed in [31]. However, most of these existing studies seldom considered the uncertainty of demands, especially that due to EV's charging demand. The studies [32–35], which integrated EVs into multi-energy systems, modeled EV travel patterns without carefully considering the randomness of EVs travel and charging or the growing penetration of EV. More importantly, the maximum capacity, i.e. the total available V2G capacity of EVs, and maximum potential of V2G, i.e. the maximum V2G power of EVs if no V2G has been executed before the appointed time, have been seldomly studied.

In order to investigate EV's charging demand and V2G potential, it is necessary to carefully consider the travel patterns and charging patterns of EVs. This is because that the accumulative impacts of EVs are far more complicated than the aggregation of individual EVs and that the accumulative charging and discharging behaviors of a fleet of EVs would create huge influences on the grid and the EH. Some previous research used simple travel information, e.g. fixed travel distance or travel time, and they obtained only fixed charging behaviors and demands [36]. Other studies that considered dynamic travel patterns often neglected the key parameters such as parking duration time and charging probability [37]. Multi agent system (MAS) has been regarded as the most effective approach for simulating random consumer behaviors and managing complex energy systems [38]. The individual units are called agents in a MAS, which take actions in a pre-defined modeling environment. The MAS has been advocated as a useful tool for smart-microgrid management [39–42], intelligent communication and control of multiple energy carriers/equipment [43,44] and optimizing EVs' charging and V2G activities [5,45]. The MAS, which is comprised of several kinds of heterogeneous agents, is often coordinated with a control architecture and the coordination is handled by an "Aggregator/Operator" agent. Therefore, many MAS simulation is also called agent-based control method in some literature [46,47]. Different from the MAS, there is another typical agent-based method, i.e. agent-based modelling (ABM)/simulation. An ABM is usually comprised of a large number of homogeneous agents [48,49] and it is thus also called individual-based model. A typical application of ABM is bass diffusion. In addition, existing literature sometimes also referred ABM to several kinds of heterogeneous agents without a global control architecture [50,51]. The management of EH with EVs is well suit to MAS implementation. To present the energy application of EVs and EH, the