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Published in:
Applied Energy

DOI:
10.1016/j.apenergy.2021.117708

Published: 15/12/2021

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Please cite the original version:
Najafi, A., Pourakbari-Kasmaei, M., Jasinski, M., Lehtonen, M., & Leonowicz, Z. (2021). A hybrid decentralized stochastic-robust model for optimal coordination of electric vehicle aggregator and energy hub entities. Applied Energy, 304, [117708]. https://doi.org/10.1016/j.apenergy.2021.117708
A hybrid decentralized stochastic-robust model for optimal coordination of electric vehicle aggregator and energy hub entities

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A R T I C L E   I N F O

Keywords:
Electric vehicle hub
Electric vehicle aggregator
Robust optimization
Alternating direction method of multipliers
Stochastic programming

A B S T R A C T

Electric vehicle aggregator (EVAGG) is an independent entity that facilitates exchanging electricity between electric vehicles (EVs) and the grid. Energy hub (EH) is another independent entity playing a remarkable role in enhancing the efficiency, flexibility, and reliability of multi-energy systems. Although interacting between various agents is beneficial to enhance their capability, it is challenging to schedule such interconnected entities. In this paper, EVAGG and EH, as independent entities, are scheduled independently and only exchange the information of electrical energy. The EVAGG scheduling is a function of EV owners’ driving patterns, including EVs’ arrival and departure times and the initial state of charge. Besides, both the EVAGG and EH operations are affected by the uncertainty of the locational marginal prices. Hence, this paper proposes a hybrid decentralized robust optimization-stochastic programming (DRO-SP) model based on the alternating direction method of multipliers to coordinate the management of entities. Stochastic programming is used to model the uncertainties of the EV’s patterns, while the uncertainties of the locational marginal prices are modeled via robust optimization to grasp the worst-case realization. Simulation results demonstrate the effectiveness of the proposed hybrid DRO-SP in terms of economic scheduling the entities while guaranteeing information privacy between entities.

1. Introduction

The economic and environmental issues have caused a movement from the conventional energy systems to the restructured energy systems with decreased use of fossil fuels [1]. In addition, the traditional systems are changing into multi-energy systems [2]. On one side, due to the synergy effects of the various energy carriers and progress in co-generation systems, which are traditionally independent, they are studied and planned independently in recent years [3]. It is also because, the multi-energy systems bring advantages, i.e. lower carbon emissions (compared to the traditional systems), high efficiency, and the capability of being interconnected with other energy types or areas. A Multi-energy system is an energy system made by coupling the links like energy generation, transmission, storage, and consumption of electricity, heat, natural gas, and other types of energy. Thus, realization of optimal scheduling and analyzing specific aspects of multi-energy systems is essential [4]. On the other side, ongoing research is focused lately on the decarbonization of the electricity generation [5] and on investment and operational decision-making of mobile and stationary supply systems in different multi-energy applications including residential and commercial, etc [6]. Meanwhile, the emerging of electric vehicles (EVs) is one of the underlying ways to replace fossil fuels with clean energy. Statistics show that only about 17000 EVs were on the world’s roads in 2010, and this number dramatically increased to 7.2 million in 2019 [7]. This willingness to use the EVs shows the potential of EVs to be an appropriate alternative for the traditional vehicles toward decarbonization of the world. In addition, in 2016, the European Environment Agency (EEA) investigated the impact of EVs on Europe’s future emissions by mentioning that if the share of EVs increases to 80% by 2050, Europe’s electricity consumption would probably face only about 10% increase [8]. One of the main upcoming challenges, with the appearance of various entities such as EH and EV aggregators, is coordination between the entities with different owners, while they share the minimum information [9]. Besides, the challenges, arisen from the uncertainty of electricity markets and driving patterns of EV owners, increase the complexity of the operation problems. Therefore, the distributed operation of different entities under uncertainty has attracted much attention lately.

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https://doi.org/10.1016/j.apenergy.2021.117708
Received 12 May 2021; Received in revised form 17 August 2021; Accepted 24 August 2021
Available online 8 September 2021
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1.1. Literature review

This Subsection highlights four primary categories of this study. First, the latest works about EV aggregation are investigated. Then, the trend of operation and optimization in EH disregarding the EH are probed. Afterward, the operation of the EH including the EVs is investigated and finally, the application of the alternating direction method of multipliers (ADMM) in energy and power systems is explored.

The authors in [10] studied a hybrid stochastic/information decision gap theory (IGDT) optimization technique for the decision-making of an EV aggregator to maximize its profit. The uncertainties related to the initial state of charge of each vehicle, arrival time (AT), and departure time (DT) were modeled via the stochastic programming (SP) and adequate number of scenarios. Additionally, the uncertainty of electricity market price in the day-ahead market was addressed by IGDT (SP) and adequate number of scenarios. Additionally, the uncertainty of electricity market price in the day-ahead market was addressed by IGDT (SP) and adequate number of scenarios. Additionally, the uncertainty of electricity market price in the day-ahead market was addressed by IGDT (SP) and adequate number of scenarios.

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tractable. Plus, the robust optimization (RO) framework was adopted to assess the costs affected by uncertainties, i.e., renewable power generations and EV charging demands. The authors in [12] proposed an optimal scheduling strategy of an electric vehicle aggregator. The investigation considered triple-level benefits of electric vehicle users, aggregators, and distribution grid. The framework of aggregated EV users’ satisfaction for services was boosted by defining a nonlinear relationship between the variation of the state of charge and satisfaction, while disregarding the existing uncertainties. A RO technique was used in [13] to offer a robust schedule of EV aggregators subject to electricity price uncertainty. The investigated EVAGG participated in the electricity market aiming at maximizing the total profit. In this work, the uncertainty of the electricity price was handled using the RO, while the uncertainty of the EV driving pattern was not included in the problem. The authors in [14] took care of coordination between two agents of EV charging stations and EVs. The interaction between the agents was developed as a non-cooperative game theory and an iterative method was deployed to obtain the equilibrium point between the agents. In addition, an SP was applied to deal with the uncertainties of RES, real-time electricity price, and traffic conditions. The idea of intelligent parking lot was presented in [15] to integrate a large number of EVs into power systems, where the problem of optimal hourly bidding curves for the intelligent parking lot was solved by a RO approach under the electricity price uncertainty. In [16] a realistic model for EVs battery was proposed for integrating the EVs into the microgrid based on the Wohler curve, concerning the degradation cost of the battery and depth of discharge. The multi-objective optimization satisfied the economic and environmental aspects, while the uncertainty of the EVs’ behaviors, wind power, electricity price, and demands were included by SP. The data-driven approach was proposed in [17] to involve electric vehicles in an ancillary service market. The EV’s charging pattern and the real-time electricity demands were subject to uncertainty. The uncertainties were analyzed using a probability prediction model to maximize the income of the EVAGG for the day-ahead schedule and providing frequency regulation service.

The optimization of EH is also a very challenging issue, and this is why many researchers are striving to develop proper methods to enhance the outcome. The authors in [18] discussed the problem of the optimal scheduling of EH to maximize the EH profit using enhanced grey wolf optimization. This work utilized the two-point estimation method to tackle the uncertainties of electricity prices, wind turbine (WT), and photo-voltaic (PV) generation as well as electrical and thermal demands. The authors in [19] investigated the planning-operation problem of the EH in addition to implementing the k-means and SP where Benders Decomposition were applied to tackle the complicated binary variables of the planning-operation problem. The authors in [20] presented an IGDT-based robust strategy for optimal on-grid EH coordination under high stochasticity of WT generation. This model minimized the total operation cost of the EH, wind power shortage cost, and carbon emissions. The IGDT approach was also deployed in [21] for optimal operation of a real EH in the LAMBDA lab microgrid, where the PV generation and electricity demands were accompanied by the uncertainties. A hybrid stochastic/IGDT optimization method was also studied in [22] to investigate the optimal scheduling of WT generations in EH. The EH operator tried to optimize the appropriate risk-seeker or risk-averse decisions using the IGDT via a mixed-integer non-linear programming (MINLP) model. The considered uncertainties included WT generations, electrical energy prices, and energy demands. Optimal self-scheduling of hydrogen-based EH was investigated in [23], where the RO was implemented to deal with the uncertainty of the electricity price. An optimal operating model for managing multiple EHs with electrical and heat energy demands was proposed in [24], considering both electrical and thermal demand response programs. The article aimed to reduce the total cost of the EH and the uncertainties of the WT generation and electricity prices were settled using the RO. The authors in [25] proposed a min–max–min robust framework for the EH-based microgrids. The column-and-constraint was deployed to handle the binary variables of the unit commitment problem and RO was utilized to handle the uncertainties of the electricity prices and renewable energy resources (RESs).

The following research investigate the centralized operation of the EH including EVs. An optimal self-scheduling of the EH was proposed in [26], where the EH operator was the owner of a parking lot within the EH. The main objective of the EH owner was minimizing the total cost in the regulation market in the presence of uncertainties of the real-time electricity price, wind power, and EVs driving pattern. The SP was developed to tackle the uncertainties via a scenario-based approach. Similarly, in [27] the authors investigated the scheduling problem of EH integrated with EV. The applied method was based on SP, while conditional value at risk (CVaR) was deployed to make a trade-off between the total operating costs of the EH and the risk-averse conditions. The driving pattern of the EVs is included using an index for the amount of power utilized in the traveling. The considered uncertainties were market prices, customer demands, wind speed, and solar irradiation managed by the k-means data cluster as the input of the problem. Similarly, the k-means and SP were applied in [28] taking into account the plug-in EVs in a residential EH as an appropriate solution to reduce the operation costs of the EH. An optimal load dispatch model for a community EH was proposed in [29] which aimed to reduce the total cost of the EH, i.e., operating and emission costs in the presence of EVs. In this study, the RO was applied to take into account the uncertainties of the electricity prices, while the arrival and departure times of the EV were addressed by the normal distribution function. A centralized operation of multi-EH was addressed in [30], including three industrial, commercial and residential EHs, where the EVs were plugged into the grid in the industrial zone. The main objective was to minimize the total operation cost from the distribution system operator (DSO) viewpoint, and the uncertainty of the driving pattern of the EVs was tackled by the SP approach. The authors in [31] investigated the EH incorporated with the intelligent parking lot to minimize the total operation cost. The driving pattern of the EVs was defined by a set of idle hours, in which when EVs were out of the parking it was called the idle hours. An operator was responsible for the centralized operation of the EH and the parking lot.

Present research also propose the application of the ADMM to optimization of energy, and power systems. The article [32] concerned a distributed multi-scenario optimization framework based on ADMM for an integrated electricity and gas system. The article established a bidirectional coupling integrated electricity and gas system model considering the dynamic features of the gas distribution system and uncertainties of RESs and load. A confidence level was considered for the uncertainties using the chance constraints to cope with the uncertainties. The article [33] investigated a distribution locational marginal price (LMP) scheme to enhance the market penetration of small-scale prosumers and consumers while improving their demand response (DR) potential considering the wholesale market and distribution network as independent entities. In this case, a multi-block ADMM distributed Douglas–Rachford Splitting method was applied to obtain the market-clearing model, while neglecting uncertainty. The authors in [34] applied an ADMM to several wind farms to minimize the network power loss, voltage deviations, and active power output deviations of wind turbines from their based power reference. The ADMM approach was used to obtain the decomposition of the centralized optimization problem into several sub-problems including wind farms. Next, the sub-problems were solved in individual local controllers with exchanged information from their practical neighbor controllers. The application of ADMM to integrated electricity and heating systems was proposed in [35] and the RO framework was developed to deal with the wind power uncertainty. In this work, the main objective was to optimize the energy and reserve co-optimization in integrated heat and electricity systems. The article [36] also studied the operation of integrated electricity and heating systems. In this
case, stochastic optimization was applied to handle the uncertainties of load and wind power, while an RO was developed to cope with the market electricity price uncertainty. Another application of ADMM was presented in [37]. The problem studied was applied to deal with the coordination of exchanged electricity between multi-microgrids and distribution networks. In this case, microgrids and distribution network were treated as independent entities, where the uncertainty of electricity market prices was settled with the RO. The authors in [38] investigated the optimal decentralized operation of the EH and natural gas system while disregarding the uncertainties.

As investigated, none of the mentioned works by the ADMM is related to the decentralized operation of EH and EV aggregator. In addition, the mentioned works in the area of EH integrated with the EVs related to the decentralized operation of EH and EV aggregator. In gas system while disregarding the uncertainties.

The survey shows valuable works related to the operation of the EH and EVAGG problems. The first part of the literature review demonstrates the operation of EVs from the viewpoint of the parking lot owner (operator), while the second paragraph investigates the operation problem from the EH owner’s viewpoint. That is, each EH or parking lot may have a different owner. Next, the third paragraph of the literature review investigates how the operation will proceed if the owner of the EVs and EHs is the same. However, to the best of our knowledge, no reported study has taken into account a decentralized model for the EH and EVAGG problem, where the owners of the EH and parking lot are different. The EH and EVAGG are often independent entities in the real world and they have their local operations. Plus, for the sake of privacy, they only exchange the border information. Therefore, it is crucial to model these entities decentralized such that, they make decisions based on their own objectives only and the shared information. The ADMM coordinates the interacting electricity between entities. In addition, in this work, for the first time so far, the hybrid robust optimization (RO) and stochastic programming (SP) model is applied to the EVAGG problem. Both the EH and EVAGG are subject to uncertainties corresponding to the LMPs in the wholesale market. In this study, the EVs uncertainty including the arrival and departure times as well as the initial state of charge of the EVs are taken into account by the SP model, while the LMPs uncertainties are considered via the RO. Such a hybrid RO-SP model not only assures consideration of the worst-case realization of the LMPs uncertainty, but also reduces the computational burden of the optimization problem. This is because, the SP is only used to handle the driving pattern uncertainties, i.e., AT, DT, and state of charge of the EVs. Therefore, the number of variables that are a function of scenarios reduces. Besides, an uncertainty budget model is proposed to control the volume of LMPs uncertainty. The proposed uncertainty budget guarantees that the problem will be robust against different volumes of uncertainty. To summarize, the main contributions of the article are as follows.

- Proposing a novel framework for the decentralized operation of the EH and EVAGG in order to coordinate the exchanged electricity between entities. The proposed model enables privacy preservation by only sharing the information of exchange of electricity between the entities.
- Presenting an uncertainty budget model for controlling the volume of LMPs uncertainty, where the entities can buy/sell to/from the wholesale market. In other words, the uncertainty budgets model is proposed to manage the robustness against the volumes of uncertainty, while both negative and positive LMP deviations are possible.
- Proposing a hybrid RO-SP model to consider the uncertainties of the EVs’ driving pattern and to reach the worst-case realization of the LMPs uncertainty.

1.2. The challenges and paper contributions

The general framework of decentralized EVAGG and EH network is depicted in Fig. 1. There is one wholesale electricity market with two different area pricing with the LMP A and LMP B, e.g., two adjacent small cities located in two different areas with their local loads. On one side, the EVAGG entity interacts with the wholesale market at LMP A and sells electricity to EV owners at a fixed tariff while also trading electricity with the EH entity with a contracted price. On the other hand, the EH entity is a large consumer that tries to minimize its total cost. To do so, the EH interacts with the wholesale market at LMP B, purchases natural gas from the gas network, and trades electricity with the EVAGG entity. A combined heat and power (CHP) and a boiler, which are used to meet the thermal demands, are fed by natural gas, while the electricity demands of the EH are satisfied by purchasing electricity from the wholesale market, generating electricity through the CHP, discharging the EH storage system (EHSS) and also by purchasing electricity from the EVAGG entity. Note that the sold and bought electricity recasts as the load and generator for each entity. It means the electricity demands of the entities may increase or decrease during some hours due to the selling or purchasing electricity from the other entity. The electricity purchased from the wholesale market at LMP A may be stored in the EHSS or transferred to the output, directly. For the sake of privacy, there is a limitation on sharing the information, and both entities only share the amount of selling/buying electricity with each other. It means each entity optimizes its objective taking into account the shared information from the other entity. It should be noted that only electricity is exchanged between entities and the other carriers, e.g., natural gas and heat are not exchanged as the parking lot does not work with other energy carriers, and it only requires electricity. Thus, the ADMM algorithm is utilized to solve the problem of entities in a decentralized model. It is worth mentioning that there is no difference between the schematic of decentralized and centralized optimizations in general. They are only different in terms of sharing information between different owners that the entities have in reality. It means two entities with different owners (operators) cannot operate in a centralized environment, and there should be an appropriate decentralized infrastructure to guarantee a proper operation. Although if the decentralized problems are solved within centralized framework, their results will be the same [35], but in this case, the centralized solution is far from reality as it will violate the privacy and independence of the owners.

Besides, the EVAGG entity is faced with the uncertainty of the arrival and departure times of the EVs as well as the initial charge state of the EVs, when they arrive at the parking lot. In addition, both entities interact with the wholesale market with uncertain LMP. As a matter of fact, dealing with such a huge number of uncertainty, which are normally arisen from combination of scenarios in SP method, makes the problem complicated and it may be intractable for the commercial software. Therefore, this paper proposes a hybrid DRO-SP model to take into account all uncertainties. The uncertainty of the LMPs is considered with the RO model, while the uncertainty related to the EVs is taken into account by the stochastic programming approach. It is worth mentioning that the size of the demands is big, and consequently their fluctuation on a large scale is negligible compared to the LMP uncertainty. Therefore, the uncertainty of the demands is disregarded in this paper.
3. Mathematical model of EVAGG and EH

3.1. EV aggregator model

The EVAGG aims to minimize its cost (or maximize its profit) by interacting with the wholesale market and EH entity as well as selling electricity to EV owners. Eq. (1) indicates the objective function, where the EVAGG can either sell to the EH entity or buy electricity in each hour at contracted price $\phi_t^{\text{con}}$. The aggregator earns profit by selling electricity to EV owners at a fixed price. The transactions with the wholesale market are subject to uncertainty. The RO is used to take care of the worst-case realization in dealing with the wholesale market. Hence, the third term of (1) maximizes the electricity prices to reach the worst-case realization in wholesale market LMP. The state of charge of each EV group is limited by its lower and upper bounds in (3). Eq. (4) assures that each EV group departs the parking lot fully-charged at $DT$. The energy used for charging the parking lot comes from the electricity bought from the wholesale market and EH entity based on (5). The parking lot energy can be discharged by selling electricity energy to the EV owners, the wholesale market, and EH entity as represented in (6). The initial state of charge of the parking lot is obtained by the initial charging state of each EV group at $AT$. The charging and discharging energy of the EVs are restricted in (7) and (8), respectively. It should be noted that a vehicle cannot be charged and discharged simultaneously [10]. The entities are connected by a tie-line and the interactions with the EH entity are limited through the tie-line discharged simultaneously [10]. The entities are connected by a tie-line respectively. It should be noted that a vehicle cannot be charged and discharging energy of the EVs are restricted in (7) and (8), respectively. The initial charging state of each EV group at $AT$ is obtained by the initial charging state of each EV group at $AT$. The charging and discharging energy of the EVs are restricted in (7) and (8), respectively. It should be noted that a vehicle cannot be charged and discharged simultaneously [10]. The entities are connected by a tie-line and the interactions with the EH entity are limited through the tie-line.
In this study, the EH is a large consumer that aims at minimizing its cost by selling/buying from/to the wholesale market at LMP, purchasing natural gas from the gas network, and interacting with the EVAGG entity. Eq. (14) indicates the objective function of the EH, where it deals with the uncertainty of the wholesale market. The RO is developed to consider the worst-case realization of the wholesale market LMP. The electrical and thermal energy balance are presented in (15) and (16), respectively. The gas entering the EH feeds the CHP and boiler by selling/buying from/to the wholesale market at LMP, purchasing with the uncertainty of the wholesale market. The RO is developed to consider the worst-case realization of the wholesale market LMP. The CHP is modeled by its feasible operation region (FOR). The FOR, where the set of electric and thermal products of the CHP are mutually dependent and the state of the charge of the EHSS is declared in (21). The state of the charge of the EHSS, charging electricity energy to the EHSS, and discharging energy from the EHSS are bounded in (22), (23) and (24). Eq. (25) indicates that the uncertainty of the wholesale market is handled via the RO approach for both entities. The EVAGG entity interacts with the wholesale market at LMP, while the EH exchanges the electricity with the wholesale market at LMP B. The entities try to maximize the deviation of the LMP from the expected value to reach the worst-case realization of the uncertainty. The objective function in (35) aims at maximizing the deviation of the LMP, while the deviation is added to the expected LMP in (36), while (37) indicates that the deviation can be either positive or negative and the total volume of the uncertainty is bounded by the uncertainty budget in (38).

The CHP is modeled by its feasible operation region (FOR). The electrical and thermal products of the CHP are mutually dependent and their dependency described by a closed region which is called FOR. Fig. 2 depicts the FOR, where the set (P, Q) stands for the coordinates of the electrical and thermal outputs. Eqs. (30)–(34) presents the constraints of the CHP feasible operation region.

The uncertainty of the wholesale market LMP is handled via the RO approach for both entities. The EVAGG entity interacts with the wholesale market at LMP A, while the EH exchanges the electricity with the wholesale market at LMP B. The entities try to maximize the deviation of the LMP from the expected value to reach the worst-case realization of the uncertainty. The objective function in (35) aims at maximizing the deviation of the LMP A, while the deviation is added to the expected LMP in (36), while (37) indicates that the deviation can be either positive or negative and the total volume of the uncertainty is bounded by the uncertainty budget in (38).

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\[
\min \sum_{t_s} p_t \left[ \sum_{s_t} E_{EH}^{\text{max}} + \max \left\{ \sum_{s_t} E_{EH}^{\text{min}} \right\} \right] \tag{14}
\]

\[
E_{EH} = E_{EH}^{\text{max}} + \eta E_{ST} - E_{EH}^{\text{min}} \tag{15}
\]

\[
h^{CHP} + h^{CHP} = H D_t \tag{16}
\]

\[
\delta_{t_s} = g^{CHP} + g^{EH} \tag{17}
\]

\[
h^{CHP} + h^{CHP} = n^{CHP} + n^{EH} \tag{18}
\]

\[
E_{EH} = E_{EH}^{\text{max}} + \eta E_{ST} - E_{EH}^{\text{min}} \tag{19}
\]

\[
0 \leq \alpha^{CHP} \leq H^{CCHP} \tag{20}
\]

\[
0 \leq \beta^{CHP} \leq B^{CCHP} \tag{21}
\]

\[
\max \sum_{t_s, \alpha} \pi a (p_{AG, t_s}^{\text{AG}} - p_{AG, t_s}^{\text{AG}}) \tag{22}
\]

\[
\phi_{t_s} = 0 \left( \forall t_s \right) \tag{23}
\]

\[
\psi_{t_s} = 0 \left( \forall t_s \right) \tag{24}
\]

\[
\delta_{t_s} = \delta_{t_s}^{\text{EH}} + \delta_{t_s}^{\text{EH}} \tag{25}
\]

\[
\psi_{t_s} = \psi_{t_s}^{\text{EH}} + \psi_{t_s}^{\text{EH}} \tag{26}
\]

\[
\phi_{t_s} = \phi_{t_s}^{\text{EH}} + \phi_{t_s}^{\text{EH}} \tag{27}
\]

\[
\psi_{t_s} = \psi_{t_s}^{\text{EH}} + \psi_{t_s}^{\text{EH}} \tag{28}
\]

\[
\psi_{t_s} = \psi_{t_s}^{\text{EH}} + \psi_{t_s}^{\text{EH}} \tag{29}
\]

\[
\psi_{t_s}^{\text{EH}} \leq 0 \left( \forall t_s \right) \tag{30}
\]

\[
\psi_{t_s}^{\text{EH}} \geq 0 \left( \forall t_s \right) \tag{31}
\]

\[
\psi_{t_s}^{\text{EH}} \leq 0 \left( \forall t_s \right) \tag{32}
\]
Similarly, the minimization version and the constraint for the EH entity, which is called entity B, are obtained as follows.

\[
\begin{align*}
\min_{\eta_{i}} & \sum_{s} \rho_s \phi_{s}^{\text{EH}} \quad \text{subject to} \\
& \phi_{s}^{\text{EH}} + \Delta^{\text{EH}} g_{\text{max}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b}\nonumber \\
& \phi_{s}^{\text{EH}} + \Delta^{\text{EH}} g_{\text{max}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b}
\end{align*}
\]  
(44)

\[
\begin{align*}
\phi_{s}^{\text{EH}} & \geq \sum_{s} \rho_s \phi_{s}^{\text{EH}} - \frac{1}{\rho_s} (\eta_{i}) \nonumber \\
& \geq \sum_{s} \rho_s \phi_{s}^{\text{EH}} - \frac{1}{\rho_s} (\eta_{i})
\end{align*}
\]  
(45)

\[
\begin{align*}
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} \\
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} \\
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} \\
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}}
\end{align*}
\]  
(46)

\[
\begin{align*}
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} \\
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} \\
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} \\
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}}
\end{align*}
\]  
(47)

\[
\begin{align*}
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} \\
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} \\
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} \\
& \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}} + \phi_{s}^{\text{EH}}
\end{align*}
\]  
(48)

4. Solution methodology

4.1. ADMM model

The ADMM algorithm is utilized when few entities can share limited information and tend to manage their belonging systems optimally. The prevalent model of the ADMM is represented as follows [38]. Eq. (49) declares the objectives of two entities subject to their equality constraint; (50) indicates the augmented Lagrangian function for the ADMM method; the variables x and z are separately optimized in ADMM using (51) and (52), and the dual variable is also updated by (53).

\[
\begin{align*}
\min f(x) + g(z) & \quad \forall x \in X, z \in Z \\
\text{s.t.} & \quad A x + B z = c \\
\min L_{a}(x, z, y) & = f(x) + g(z) + y^{T} (A x + B z - c) \\
\frac{\partial}{\partial x} & \quad A x + B z - c \| 2 \quad \forall x \in X, z \in Z
\end{align*}
\]  
(49)

\[
\begin{align*}
x^{k+1} & = \arg \min_{x} L_{a}(x, z^{k}, y^{k}) \\
z^{k+1} & = \arg \min_{z} L_{a}(x^{k+1}, z, y^{k}) \\
y^{k+1} & = y^{k} + a (A x^{k+1} + B z^{k+1} - c) \quad \forall x \in X, z \in Z
\end{align*}
\]  
(50)

(51)

(52)

(53)

4.2. Decentralized management model of EH and EV aggregator

The centralized optimization problem needs a unified entity, but in reality, the EH and parking lot are the assets of different entities (owners) in many real cases. For the sake of privacy and communication limitations, only border information can be exchanged between the two entities [36], and decentralized algorithms can deal with such conditions. Hence, the ADMM algorithm is utilized, which decomposes problems with separable variables to small local sub-problems to find the optimal solution for large-scale problems [40]. In this work, the EH and the EVAGG are entities that manage their belonging systems, while they only know about the energy exchanged through the tie line presented in Fig. 1.

The ADMM is an iterative algorithm and it coordinates the exchanged energy by knowing the problem of each entity. In other words, the ADMM is utilized to remedy the conflict of the transacted electricity between two entities. To do so, the problem of each entity and the variables are represented as follows.

4.2.1. Problem of EV aggregator in ADMM framework

The EVAGG interacts with the wholesale market at LMP A and EH entity to exchange electricity as well as selling electricity to EV owners. The total cost of the EVAGG problem is minimized taking into account the interactions with the EH entity. The objective function of the EVAGG entity in the ADMM framework is represented as follows.

\[
\begin{align*}
\frac{\partial}{\partial z_{i}} & \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \\
\frac{\partial}{\partial z_{i}} & \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \\
\frac{\partial}{\partial z_{i}} & \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \\
\frac{\partial}{\partial z_{i}} & \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}} \quad \frac{\partial}{\partial z_{i}}
\end{align*}
\]  
(54)

Note that the cost of trading with the wholesale market is replaced with the equivalent dual function obtained in (39).

\[
\begin{align*}
\min & \sum_{i=1}^{N} \rho_i \sum_{t=1}^{T} \sum_{s=1}^{M} \sum_{t=1}^{T} \sum_{s=1}^{M} (f_{EH}^{AGG} - p_{EH}^{AGG} + \\
& \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b} \\
& \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b} \\
& \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b} \\
& \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b} \\
& \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b}
\end{align*}
\]  
(55)

Subject to (2)–(13) and (40)–(43).

4.2.2. Problem of EH in ADMM framework

To obtain the ADMM objective function for the EH entity, the augmented Lagrangian function is added to the objective function (14) as follows. It is worth mentioning that the cost of trading with the wholesale market is replaced with the equivalent dual function calculated in (44).

\[
\begin{align*}
\min & \sum_{i=1}^{N} \rho_i \sum_{t=1}^{T} \sum_{s=1}^{M} \sum_{t=1}^{T} \sum_{s=1}^{M} (f_{EH}^{AGG} - p_{EH}^{AGG} + \\
& \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b} \\
& \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b} \\
& \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b} \\
& \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) - \Delta^{\text{EH}} g_{\text{min}}(\eta_{i}) + \Gamma m_{b}
\end{align*}
\]  
(56)

(57)

(58)

For better comprehension, Fig. 3 presents the flowchart showing the procedure of the proposed decentralized framework, where the steps of the RO and ADMM are specified separately.
5. Numerical results

5.1. Case study

Simulations are carried out in Fig. 1 to evaluate the effectiveness of the proposed model. The hybrid DRO-SP is implemented to solve the decentralized scheduling of the EVAGG and EH with a 24-h time horizon. It is tried to take the input data from realistic references as much as possible. It can be deduced that the driving pattern including the arrival/departure time to/from the parking lot as well as the initial charge state of the EVs affects the scheduling procedure significantly. Therefore, the SP has been applied to take care of the uncertainty related to the EVs. To do so, generated and reduced scenarios in [10] is used as given in Table 2, where the Gaussian distribution function has been used to generate the scenarios. The earliest arrival time is 5:00 and the latest departure time is 22:00. For the sake of simplicity, it is assumed that the EVs do not leave the parking lot between the arrival and departure times. Table 3 provides the main details of the five EV types used in this study [10,41]. The total number of EVs is 2000, while their number changes in the parking lot, and it depends on the AT and DT of the EVs [26,42]. Since the AT and DT are different in various scenarios, the number of EVs that are plugged into the parking lot changes over the time. The price of selling electricity energy to the EV owners is set to a fixed value of 35 $/MWh [26]. The provided LMPs of the wholesale markets in Fig. 4 have been taken from [43]. The presented LMPs are taken into account as the expected value for the RO approach. During the hours 1–7 and 19–24, the LMP $A$ (LMP of the EVAGG) has higher prices compared to the LMP $B$ (LMP of EH). It is assumed that the contracted price between the two entities is equal to the average of the LMPs. The electricity and heat demands have been shown in Fig. 5. Since the fluctuation of the gas price is negligible within 24 h, the gas price is assumed to be fixed by 22 $/MWh [39]. The boiler maximum capacity is equal to the peak value of the heat demands and the CHP FOR coordinates are derived from [23]. The other essential characteristics of the problem have been given in Table 4. The mathematical Mixed-Integer Quadratic Conic Problem (MIQCP) has been carried out by CPLEX solver under GAMS version 34 [44].
5.2. Discussion

This section provides the numerical results of the proposed hybrid DRO-SP model. Fig. 6 demonstrates the expected and robust LMPs. The robust LMP of the EVAGG does not change during hours 1–6 and 22–24 due to the arrival and departure times of the EVs, i.e., no EV arrives before hour 5 and no EV departs after hour 22. It is worth mentioning that the aggregator can use the charge of the EVs one hour later than they arrive in the parking lot. It means the earliest EVs arrive at 5:00, while the earliest charging is shown at 6:00. It is because the time interval is considered hourly and an EV is plugged into the grid when it arrives at the parking lot, but its first charge amount can be shown by the mentioned slot. It means when an EV arrives at the parking lot at 5:00:01”, it connects, and its first charge is revealed at 6:00:00 due to the time slot. In the other intervals, the robust LMP of the EVAGG increases except for hour 18. According to Fig. 7, hour 18 is the only hour that EVAGG sells electricity to the wholesale market. In other words, the robust LMP of the EVAGG raises when it buys electricity from the wholesale market and decreases when it sells electricity. It accounts for the worst-case realization of the LMP uncertainty, i.e., selling electricity at the lower price and buying electricity at the higher price. Regarding the robust LMP of the EH in Fig. 6, the robust LMP often increases to reach the worst-case realization of the LMP $B$ where the electricity energy is only purchased from the wholesale market and no electricity is sold to the wholesale market according to Fig. 8. This occurs because, according to Fig. 9, in the interval between 8:00 and 15:00 h, the EH itself needs electricity to supply its electricity demands. On the other hand, the EH prefers selling electricity to the EVAGG entity in hours 6:00, 7:00, 18:00, 20:00, 22:00 where the EVAGG offers higher prices compared to the wholesale market.

According to Eq. (4), the EVAGG has to fully charge the EVs before they depart the parking lot. Fig. 10 verifies that the electrical energy is sold to EV owners only when the EVs depart the parking lot in the interval from 17:00 to 22:00 h. Fig. 11 shows the charging/discharging of the aggregated batteries. The significant part of the discharging occurs when the EVs depart the parking lot, in interval from 17:00 to 22:00 h, and the other part is conducted when the electricity energy is sold to the EH entity (interval 8–16). The batteries are also charged when the electricity is purchased from the EH entity and the wholesale market as shown in Fig. 7. According to Fig. 12, EHSS charges in the off-peak interval of the EH LMP (LMP $A$) and discharges in the peak interval of the LMP where the electricity price is higher. Fig. 13 demonstrates the gas entering the EH, gas entering the CHP, and the boiler. Based on Fig. 13-b, no gas is entered the CHP between hours 2–5. It means no electricity is generated through the CHP in this interval. It is due to the lower price of the LMP $B$ in this interval compared to the natural gas price. As a result, the electricity demands are only met by the wholesale market in this interval. Fig. 13-c shows the gas entering the boiler as the main source of supplying the heat demands. Fig. 13-a is also can be obtained by collecting the 13-b and 13-c based on Eq. (17).
To better assess the ADMM algorithm, the convergence of the total costs of the entities has been given in Fig. 14. Fig. 14-a shows how the convergence criteria is met and how the differences defined in (55) reach the predefined tolerance. As can be seen from Fig. 14-b and Fig. 14-c, the costs of the entities are accompanied by fluctuation while the fluctuations decrease gradually within 131 iterations.

Table 5 provides the sensitivity analysis on the robustness of the proposed model against different volumes of the LMPs uncertainty budget. The number of hours allowed to be subject to uncertainty
Sensitivity analysis on uncertainty budget of LMPs.

| $N_p$ | Profit of aggregator ($) | Cost of EH ($) |
|-------|--------------------------|----------------|
| 0     | 15262                    | 112969         |
| 6     | 12139                    | 118257         |
| 12    | 9168                     | 119980         |
| 18    | 9052                     | 124000         |
| 24    | 8988                     | 124222         |

($N_p$) changes from 0 to 24 where 24 means all hours affected by uncertainties and 0 means no uncertainty is considered for the LMP. Increasing $N_p$ decreases the profit of the EVAGG from 15262 to 8988 $ while it increases the cost of the EH entity from 112969 to 124222 $. The LMP goes up (during most of the hours as shown in Fig. 6) by increasing the $N_p$. It results in purchasing electricity from a more expensive resource (the wholesale market) and consequently, it increases the total cost of the EH and decreases the profit of the EVAGG. It means that the problem is robust with different uncertainty budgets, although, with more/less cost/profit. Indeed, the sensitivity analysis proves the efficiency of the proposed model in dealing with the different situations, i.e., deviations of the input expected LMPs. Moreover, since the proposed framework seeks for the worst-case realization of the LMP in the wholesale market, if the model is robust under the worst-case condition, it will be definitely robust against other realization of LMPs. Normally, an energy buyer (seller) tends to buy (sell) its required energy at a low (high) price. In the worst-case realization, the problem is solved for the possible highest (lowest) LMP, when the electricity is purchased (sold). It means, when a mathematical solution exists for the highest (lowest) LMP for purchasing (selling) electricity, the solution will definitely exist for the lower (higher) prices [45]. For instance, if the EH operator can afford to buy electricity in hour 12 by 45 $/MWh (worst-case), it can certainly afford to buy it at lower prices (see Fig. 6).

Table 6 is provided to elaborate on the scalability of the proposed mathematical framework focusing on the computational complexity. The order of complexity and the current size of each entity model is given in this table. The second column demonstrates the order of complexity, which directly depends on the sets in the problem, i.e., scenarios, time, and EV types. The last column stands for the current size of each variable and constraint considering the current size of the sets in the problem. It can be seen from this table that the model is quite complicated with a large number of constraints and variables, and the bigger the size of the sets are, the more complex the problem becomes. It is noteworthy to mention that the computational time for the current size of the problem is 351 s.

6. Conclusion

In this paper, a hybrid distributed robust optimization-stochastic programming (DRO-SP) framework has been proposed to investigate the robust operation of two independent entities of electric vehicle aggregator (EVAGG) and energy hub (EH). The alternating direction method of multipliers (ADMM) has been utilized to coordinate the electricity energy exchanging between the entities taking into account the privacy issues. The EVAGG deals with the uncertainties of the arrival and departure times of the EVs as well as the initial charges of the EVs, when they arrive at the parking lot. In addition, the entities interact with the wholesale markets with uncertain locational marginal prices (LMPs). The developed model takes into account the uncertainty of the EVs via stochastic programming and maximizes the LMPs deviation using the robust optimization approach, and then the ADMM method is applied. Results show that the robust LMPs raise when the entities purchase electricity and decrease when the EVAGG sells electricity to the wholesale market in order to reach the worst-case realization of the LMP uncertainties. Besides, the EH entity prefers selling electricity to the EVAGG entity, when it has surplus energy, due to the higher exchanging price between entities compared to the wholesale market. The EVAGG charges fully the EVs when they depart the parking lot. It means the parking lot capacity is discharged to supply the battery of the EVs to reach the full charge when they depart the parking lot, while the charge of the parking lot increases when the EVs arrive at the parking lot. On the contrary, the charging/discharging pattern of the EHSS depends on the LMP signal and it charges and discharges based on the off-peak and peak prices, respectively. Moreover, the CHP does not generate electricity in the intervals that the LMP of the wholesale market is more reasonable to purchase compared to the natural gas price. The sensitivity analysis on the uncertainty budget of the LMPs shows that the problem is robust against different volumes of the uncertainties, although the cost of the EH entity increases and the profit of the EVAGG decreases by increasing the uncertainty budget. Finally, analyzing the results of the ADMM algorithm demonstrates reaching the small tolerance number verifying the appropriate coordination between entities.

A networked constrained decentralized framework for the operation of EVAGG problem and EH operation will be considered as the prospect of future work, where the vehicle-to-grid mode, as well as the effects of electricity and natural gas on the utility level, will be investigated.
Acknowledgment

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Linearization of absolute value function

The maximization model of the deviation of the LMP $\phi$ makes non-linearity because of the presence of the absolute function. First of all, the inequalities (37)–(38) are reformulated as follows.

$$x_i^{\text{in}-\text{out}} = x_i^{\text{in}} + \phi_{x_i} \leq \frac{a_i}{\gamma_i} \quad \text{(A.1)}$$

$$\psi_x \leq \frac{\Delta^{\text{max}}}{\gamma_i} \quad \text{(A.2)}$$

$$\psi_x \geq -\frac{\Delta^{\text{max}}}{\gamma_i} \quad \text{(A.3)}$$

$$\sum_{i=1}^{T} \psi_{x_i} = 0 \quad \text{(A.4)}$$

$$\sum_{i=1}^{T} \phi_{x_i} \leq \frac{\lambda_p}{\psi_x} \quad \text{(A.5)}$$

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