A Decentralized Electricity Trading Framework (DETF) for Connected EVs: A Blockchain and Machine Learning for Profit Margin Optimization

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***Abstract*—Connected electric vehicles (CEVs) can help cities to reduce road congestion and increase road safety. With the technical improvement made to the battery system in terms of capacity and flexibility, CEVs, as mobile power plants can be an important actor for the electricity markets. Especially, they can trade electricity between each other when supply stations are full or temporarily not available. In this article, we propose an advanced decentralized electricity trading framework between CEVs in parking lots based on consortium blockchain, machine learning, and Game theoretic model. We design a distributed smart contract solution based on a stochastic bidding process, which helps CEVs to sell and buy electricity with their maximum profitability. Finally, numerical simulations with MATLAB and Solidity are conducted to prove the effectiveness of our proposed solution. Also, a comparison with another method in terms of CEVs' profitability improvement and energy trading management is provided.**

***Index Terms*—Blockchain, connected electric vehicle, decentralized energy trading, decentralized ledger technology, distributed data, game theoretic, machine learning (ML), peer-to-peer (P2P) transactions, profit margin, smart contract.**

I. Introduction

CONNECTED electric vehicles (CEVs) [1]–[3] are expected to help cities to manage several problems related to public safety, public services, transportation, and energy. They can be in near future the norm in automobile industry by their expected substantial technological and socioeconomic development in the city, especially for their impact on power management. Added to its benefit in term of oil dependence and Greenhouse Gas (GHG) emissions reduction, the CEV, as part of smart city concept will be one of the most important challenging issues for demand response (DR) systems in smart grid. Indeed, as it is a new division in the automobile industry by the zero emission and low noise [4]–[7], CEV can help in the grid stability by its charging or discharging operations. The CEV can reduce the overloading situation of reginal transformers as well as offering ancillary services such as frequency and voltage fluctuations regulation [6]–[8].

According to the International Energy Agency (IEA) the number of hybrid and battery-electric vehicles grew to a stock of two million EVs worldwide by the end of 2016. This number is expected to reach 60 million by 2030 [9]. As a result, a high CEV penetration can make the data and electricity management more challenging. To deal with this idea, facilities for CEV integration to smart city have to be designed in the way promote economic and social welfare issues around the data exchanging and electricity routing. The CEV can be a great candidate for easy electricity trading deployment [10], [11] and for efficient new business models around the charging needs. It can be considered as an enabler for the decentralization of the electricity and or data by replacing central services in microgrid system such as load balancing, DR management, frequency, and voltage regulation, etc. The CEV can accelerate the transition to smarter electricity system by allowing new business model based on social welfare and profitability maximization, auctions (i.e., the ascending-bid auction, the descending-bid auction, the first-price sealed-bid, and the second-price sealed-bid auction), economic incentive mechanisms and peer-to-peer (P2P) electricity markets. However, the current electricity system is a major handicap to establish an efficient trading energy process between neighbors. First, because it uses a centralized architecture which obligated neighbors to sell electricity back to the grid before getting payed at a regulated low price with delay time. Second, it forced sellers and buyers to expose their real profile information during the trading process, which is crucial for CEV users' privacy and parking lot safety as a part of the global security in the city. The blockchain technology which recently attracted investors and governments is expected to resolve these issues and transform the way to make business. Blockchain which is known by its first application in finance: the Bitcoin [12], [13], is a decentralized peer-to-peer (P2P) network of database where all participants can perform P2P transactions without any central authority. The last is replaced by the techniques of sharing responsibility and distributing trust to verify the transaction legibility. The blockchain can be public, private, or consortium network [13]. It presents a huge potential in enhancing current value chains and making new ones that eliminate intermediation cost with trust and transparency improvement

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[14], [15]. With its specific application called smart contract used for example by Hyperledger and Ethereum blochchain platforms, blockchain technology can be used in several sectors such as healthcare, financial industries, insurance, storage of medical records, security, education, Internet-of-Things (IoT), and electricity management. For example, blockchain can be simply used to promote the electricity trading [16]–[21] for microgrid and between CEVs as mobile power plants in the city. Indeed, the CEV sellers of electricity can get paid immediately and the electricity transaction will be more efficient and trustworthy and more secure as it is P2P market without any trusted third part (intermediaries). Kang *et al.* [22] proposed the PETCON which is a consortium blockchain scheme for a local P2P electricity trading model between plug-in hybrid EVs (PHEVs) based on double auction mechanism for the price negotiation between players. It is proven that double auction mechanism [23] is suitable for a large number of market participants with fast demand and supply fluctuation; this case is far from the real trading electricity market where the number of sellers and buyers can be limited. However, game theoretic (GT) models deal deeply with the competitive situation of the market based on bidding strategies and individual preferences. Moreover, double auction models present hard nonlinearities, which grow complexity in the analysis phase compared to the empirical approaches.

In other hand, as a part of Artificial Intelligence, the machine learning (ML) techniques are used to improve the data management for smart cities issues using vehicles [24]. The ML mechanisms are expected to improve the efficiency of schemes or iterative algorithms by analyzing the execution process and suggesting new features to identify or to update variables and incorporate them in the future iterations. Adding ML to blockchain capabilities in electricity trading can provide deeper analysis of market data and can bring more effectiveness to smart contract to increase the profitability of participants.

In this article, we propose an advanced trading electricity framework for CEVs in parking lots. This system is based on blockchain, ML and GT system to overcome the need to the mandatory trust third part in traditional market and to improve the smart contract efficiency and to optimize the profit margin for CEVs.

Our contributions are as follows.

1) We are the first to consider the combination of Blockchain, ML, and GT in electricity trading system and we propose a decentralized electricity trading framework (DETF) in parking lots between CEVs.
2) We develop the HLProfitX algorithm as an adaptive bidding system based on ML and GT approach for CEVs to sell and buy electricity with their maximum profitability using the new cryptocurrency HAPPY LIGHT Coin (HLCoin).
3) Finally, numerical simulations are presented to prove the effectiveness of our proposed solution.

The rest of this article is organized as follows. In Section II, we present some related works. Section III presents the system overview considered in this article. In Section IV, we formulate our proposed smart contract model. The performance evaluations are presented in Section V. Finally, Section VI concludes this article.

II. Related Works

A. Electricity Trading

Recently, the literature review of the trading energy in context of smart grid is being vast and covers various aspects of energy management in centralized and distributed ways. For example, a trading energy schemes are proposed by [25] and [26] based on centralized technique where all participants are aggregated. These mechanisms show their limits especially when individual participant wants to trade a few amount of electricity with a real-time constraint in an open market according to a bidding process between sellers and buyers. Indeed, added to the non-competitiveness business process when the central unit forced all participants to use the regulated electricity price, a real issue exists on the users' personal data protection because the aggregation process is a one failure point.

Kou *et al.* [27] proposed an energy trading model based on game-theoretic approach between utility and microgrids during the restoration period. Added to the aggregation mechanism used between all players, the economic strategy of this scheme considers a reduced voltage stability effects on each player. The model does not consider EVs participation in such market. To cope with the problem of the centralized architecture, several studies focus on peer-to-peer (P2P) trading energy [28], [29]. Indeed, to reduce the impact of the EVs penetration on the smart grid and their total daily energy cost, Alvaro-Hermana *et al.* [28] proposed a P2P energy trading system between EVs. This scheme does not take onto account the maximization of service provider benefits in context of applicable business models.

B. Blockchain-Based Energy Trading

The blockchain as a new distributing trust network is highlighted by four main features such as the data integrity, the security, the trustiness, and the decentralization approach. The blockchain is expected to modernize the grid and to be part of energy industry by developing the electricity trading especially the P2P energy transaction. Many industrial approaches addressing decentralized electricity management using blockchain are started. For example, in 2016 the first known project in this topic is the Brooklyn microgrid in New York [17]. Indeed, the electricity provided by solar panel can be traded between home neighbors and a smart contract based on Ethereum blockchain is used for the energy and payment transaction. Another project is the German RWE, which uses blockchain to develop the interaction between public supply stations and electric vehicles (EVs) [16]. There are some research efforts, which match the energy management with the blockchain technics. For example, Horta *et al.* [19] proposed virtual distributed grid based on blockchain to allow homes to transact energy with neighbors. Also Zhang *et al.* [20] presented blockchain applications in context of Internet of Energy (IoE). We mention that for all these industrial or scientific works, there is no transaction between electric cars directly. Sharma *et al.* [30] presented a system of Internet of

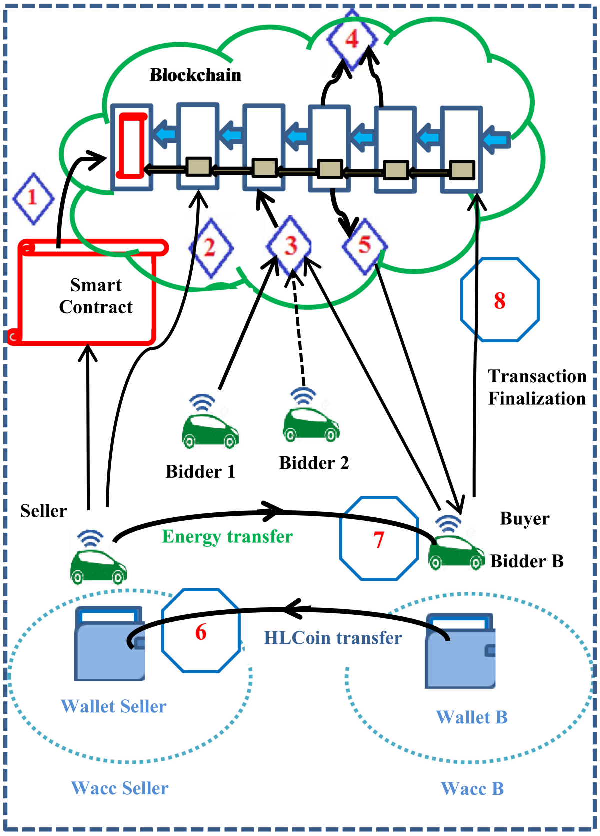

Fig. 1. Conceptual blockchain architecture for our DETF.

Vehicle (IoV) able to exchange energy by a blockchain energy-efficiency transaction. The authors do not show any effective results to prove their proposed system. A recent paper [31] proposed a blockchain-based energy trading scheme to supervise and manage the energy trading process. The work presented in [32] proposes a contract-based energy blockchain for secure EV charging in Smart Community. However, for all these three last papers, the proposed schemes are concentrating on the security and fairness issue during the P2P energy trading while not considering the profitability maximization for the participants in this energy market.

In this article, we propose a new DETF between CEVs in parking lots based on consortium blockchain, ML, and GT model with stochastic approach.

III. System Overview

In this section, we consider a system such as illustrated in Fig. 1, where a number of CEV sellers and CEV bidders of electricity are sharing a parking infrastructure area equipped by an activated blockchain server. Furthermore, we suppose that CEVs can communicate wirelessly between each other's. We assume that each CEV is equipped by its own smart meter that determines the quantity of electricity sold or purchased during a period of time. Also, CEV sellers and bidders can sent/receive messages to/from blockchain server. We suppose a consortium blockchain based on Hyperledger platform, which provides a cryptocurrency such as HLCoin as a new decentralized digital currency used to manage energy credits and to monetize or trade any services, goods, and commodities between CEVs.

We suppose that each CEV (electricity seller or buyer) has a unique identity number (*IdN*), which is communicated to the blockchain server at the beginning. Also, all participants (CEV buyers, sellers) receive from the blockchain server their public and private encryption keys (*public_K, private_K*) used for addressing and sending signed transaction. We assume that the blockchain server can verify and certify the identity of CEVs and their wallets *Wacc* (cryptocurrency account). Also, it verifies the authenticity and privacy [33], [34] of any transaction.

In this article, we focus on the auction mechanism as a part of the smart contract which is used for our decentralized electricity trading system.

Our model is based on three elements: CEV seller, CEV bidder, and smart contract. Fig. 1 shows our proposed architecture for electricity trading between CEVs.

Indeed, there are eight events used to explain the data and electricity exchange between CEVs, blockchain, and smart contract:

1) a smart contract is made between all stakeholders and deployed to the blockchain;
2) New auction is made: a CEV seller which wants to sell electricity stored in its battery, informs the blockchain by its available quantity of electricity for selling;
3) CEV bidders will submit their bids;
4) smart contract runs an auction model (based on electricity requested information or game theory) to determine the winner and price;
5) the selected CEV bidder is awarded the electricity;
6) the seller is awarded by HLCoin;
7) the electricity transaction is initiated; and
8) the transaction is finalized.

Fig. 2 shows the conceptual data blocks used in our DETF. The block number identifies the current block, the hash, and the previous block fields are the hash values describing the current block content and the previous one, respectively. The transaction field designates the exchange process between CVE buyer and seller. The creation timing and the size of the current block are stored respectively in timestamp and size field. The merkle root field is the hash value of all previous hashed pair in the tree.

For the block building mechanism, after the creation of the genesis block (the first one), a participant (CEV seller or buyer) which is interested on the electricity trading in a parking lot and after ensuring its identity, it can create a new block, linked it to the chain and broadcast it on the network. Receiving this block by the other participants, they proceed on its validation by verifying the signature, checking the hash, and checking the validity of the payload. The last action is used to ensure that data are protected from unauthorized modification. The valid block will be added to the chain and it cannot be tampered. The invalid block will be discarded from the chain.

In our proposed energy trading system, we suppose that an efficient communication network system with secure privacy preservation mechanism is used to link all participants in the trading system. As a result, we consider that there is no problem with CEV's privacy in this article.

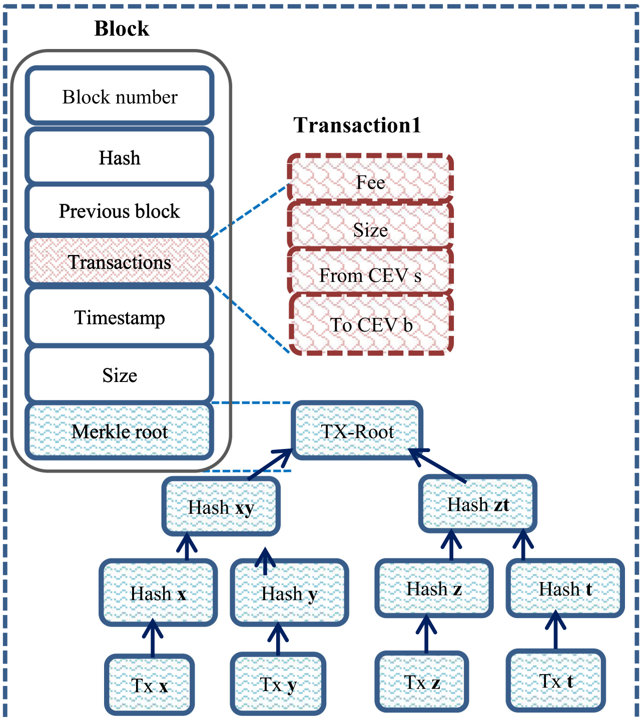

Fig. 2. Conceptual data block in our DETF.

We acknowledge that in terms of reliability, performance, and smart management, the DETF needs an increased connectivity that could result in security and privacy issues such as the risk of cyber-attacks which can be a challenging problem for the electricity trading system in parking lot. The CEVs ‘ Privacy is the practice of protecting confidential data and information about CEV's behaviors, location, interests, etc., to others who have no authorization to see such data or information. Technically, privacy is a mechanism to protect personal data and it is typically realized by anonymization, obfuscation, differential privacy, and cryptography [35], [36]. The CEV's privacy issues could slow down our DETF deployment in realistic scenario. The DETF's communication system needs to be trusted by providing a secure environment to allow for privacy data to be used to perform trading process between CEVs correctly.

IV. Smart Contract Model

The smart contract is a digital protocol that simplifies the agreement process between different participants by imposing predefined clauses such as the auction and payment functions.

This contract has to be accepted by all remaining parties (CEV sellers and buyers) by signing an acceptance in the beginning of the connection to the blockchain server at the parking lots. As presented in Fig. 3, the data bidder is composed of Bidder profile (a cryptographic key representing the ownership of the CEV), the quantity of electricity requested, the transaction timing and the price. The data seller is composed of seller profile (a cryptographic key represents the ownership of the CEV), the surplus quantity of electricity to be sold, and the transaction timing. Every CEV buyer submits multiple bids to the blockchain. The

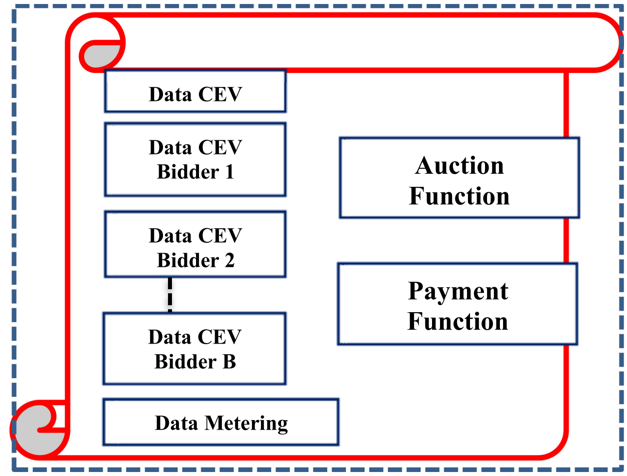

Fig. 3. CEV smart contract.

CEV buyer needs at most one seller, and we assume that no duplicate bids can exist on the same CEV seller.

In the following, we present the details of our auction technics used in this article. We suppose that a set of CEV buyers with their corresponding quantity of energy requested and CEV sellers with their corresponding energy to sell can be written as follows:

$$NC_b = \{1, 2, \ldots, N_b\} \tag{1}$$

$$P_b = \left\{P_{b_1}, P_{b_2}, \ldots, P_{b_{N_b}}\right\} \tag{2}$$

$$NC_s = \{1, 2, \ldots, N_s\} \tag{3}$$

$$P_s = \left\{P_{s_1}, P_{s_2}, \ldots, P_{s_{N_s}}\right\}. \tag{4}$$

Each CEV calculates the quantity of the power needed to buy or ready to be sold by taking into account its current battery lifetime, the degradation coefficient, and its depth-of-discharging (DoD). To simplify our model, we suppose that the factors influencing the CEV battery life such as extreme temperatures, overcharging, the charging, and discharging rates are not considered in this article.

A. Auction Model Based on Energy Requested Information

The energy transaction in the open local electricity market such as the parking will happen after receiving the information of: 1) the energy dedicated for selling from CEV sellers and, 2) the electricity requested for CEV buyers.

The energy transactions for the CEV sellers highly depend on behavior of all participants (the battery CEV capacity, SoCs) and their individual preferences in terms of the tariff structure and timing. Each CEV seller usually calculates their own benefits before energy transaction in the open market. The CEV sellers need to conduct the cost-benefit analysis considering different price policy.

A CEV buyer will participate in the local energy transaction if the rate is lower than the utility grid (r_g). Also, car seller will sell it surplus electricity to CEV buyers if the price is greater than

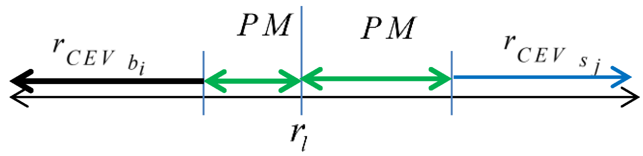

Fig. 4. Price limit, profit margin relation for each CEV trader.

Algorithm AMERI: Auction Model based Energy Requested Information.

Input: $NC_b, NC_s, P_b, P_s, r_{fg}, r_{let}, r_g, \rho_{CEV_b}$
Output: CEV sellers selected

1. CEV sellers declare their surplus electricity quantity and their range of tariff.
2. According to its priority level defined by 6 and its preference (the quantity of electricity requested, the transaction timing and the price.), each CEV buyer selects the adequate car sellers. /* CEV buyer can buy from one or several CEV seller*/
3. Start payment process
4. Start energy transaction

the feed-in tariff (r_{fg}). Therefore, the rate of the local energy transaction (r_{let}) can be written as follows:

$$r_{fg} \leq r_{let} \leq r_g. \tag{5}$$

The priority for the energy transactions in the open local electricity market in the parking lot is based on the energy shortage of different cars. Indeed, the CEV with the lowest energy requested has the highest priority for purchasing energy from car sellers in the same parking lot. Thus, each car with energy requested is sorted and ranked in the ascending order of energy shortages. Thus, the priority vector of energy requested of different cars can be written as follows:

$$\rho_{CEV_b} = [\rho_1 \quad \rho_2 .. \quad \rho_M]^T \tag{6}$$

where ρ_1 is the priority assigned to the car with the lowest energy shortage and ρ_M is the priority assigned to the CEV with the highest energy requested.

The overall benefit of this local energy trading in the same parking is analyzed based on (5). A biding and competitions process is running before the electricity transaction.

B. Adaptive Bidding Based on ML and Game Theoretic Approach

In this section, first we consider a predictive bidding approach (PBA) based on stochastic bids, which are able to learn from the current electricity market environment by including iterations of the profit margin (PM). Each CEV trader (seller or buyer) tries always to maximize its PM (see Fig. 4) and announces the adequate bidding price [35].

Second, we present our game theory approach to match the CEV sellers ($j \in NC_s$) with the CEV buyers ($i \in NC_b$).

Each CEV trader determines its next price (r_{CEV}) based on the price limit (r_l) and the profit margin according to the following equation:

TABLE I
Profit Margin Variation

	PM
CEV Seller	$[0, +\infty)$
CEV Buyer	$[-1, 0]$

TABLE II
Parameter $r_{t\arg}$, R and L Variation

	$r_{t\arg}$ increases	$r_{t\arg}$ decreases
L	$[0; 0.05]$	$[-0.05; 0]$
R	$[1; 1.05]$	$[0.95; 1]$

$$r_{CEV}(n) = r_l\,[1 + PM(n)] \tag{7}$$

where n is the iteration index. Equation (7) shows that the margin and profit for the CEV seller follows directly the PM variation: it increases /decreases when the PMincreases /decreases. The case is opposite for the CEV buyer and its margin and profit follows inversely PMvariation (see Table I).

The $PM$for the next period is given by

$$PM(n+1) = \frac{r_{CEV}(n) + \sigma(n)}{r_l} - 1. \tag{8}$$

The parameter $\sigma(n)$ describes the variation between the current price and the next one. This parameter is modeled as

$$\sigma(n) = \gamma\sigma(n-1) + (1-\gamma)\Delta(n) \tag{9}$$

where γ is the weighting coefficient which describes how the profit is altered. The parameter $\Delta(n)$is the Widrow–Hoff delta [30], which designs the variation between the current price and the target one. This parameter is given by the following equation:

$$\Delta(n) = \beta\,[r_{t\arg}(n) - r_{CEV}(n)] \tag{10}$$

where β is a learning rate coefficient. The price $r_{CEV}(n)$ converges to the target price $r_{t\arg}(n)$ at speed of β.

The target price is modeled as

$$r_{t\arg}(n) = R(n)r_q(n) + L(n) \tag{11}$$

where r_q is the last announced price (last iteration), R and L variation is given by

$$\begin{aligned} R(n) &= R(n-1) + \tfrac{R_{\max}}{step} \\ L(n) &= L(n-1) + \tfrac{L_{\max}}{step}. \end{aligned} \tag{12}$$

$R_{max}, L_{max}$and $step$ are a setting parameters (see Table II and Algorithm HLProfitX).

Now, as a result of the iterations described by (7) to (12), each CEV sets a selling//buying price (r_{CEV}) based on information from the current electricity market environment. The energy dedicated for selling P_{s_j} $j \in NC_s$ can be distributed between different CEV buyers $i \in NC_b$, through a portion λ_i. It can be written as

$$P_{s_j} = P_{s_j} \sum_{i \in NC_b} \lambda_i. \tag{13}$$

The utility of the CEV seller$j$ can be given by the following equation:

$$\psi_j(P_{s_j}, P_{s_{-j}}) = P_{s_j} r_{CEV_{s_j}} \sum_{i \in NC_b} \lambda_i \tag{14}$$

where $P_{s_{-j}}$ is the vector of energy dedicated for selling for all sellers other than j.

The main objective of the CEV sellers is to maximize the sum of utilities for individual CEV sellers and the objective function can be written as follows:

$$\max_{r_{CEV_{s_j}}, j \in \mathrm{NC}_s} \left(\sum_{j \in \mathrm{NC}_s} \psi_j(P_{s_j}, P_{s_{-j}}) \right)$$

$$= \max_{r_{CEV_{s_j}}, j \in \mathrm{NC}_s} \left(\sum_{j \in \mathrm{NC}_s} P_{s_j} r_{CEV_{s_j}} \sum_{i \in \mathrm{NC}_b} \lambda_i \right)$$

Subject to : $P_s \leq P_b, r_{CEV_{s_{\min}}} \leq r_{CEV_{s_j}} \leq r_{CEV_{s_{\max}}}$ and

$$P_{s_j} = P_{s_j} \sum_{i \in \mathrm{NC}_b} \lambda_i \tag{15}$$

where $r_{CEV_{s_{\min}}}$ and $r_{CEV_{s_{\max}}}$ are the minimum and the maximum rate of selling electricity respectively fixed by the CEV sellers.

In the same time, the CEV buyer $i \in NC_b$ can purchase energy from different sellers $j \in NC_s$, through a portion δ_i. It can be written as

$$P_{b_i} = P_{b_i} \sum_{j \in NC_s} \delta_j. \tag{16}$$

The utility of the CEV buyer i can be written as follows:

$$\varphi_i(P_{b_i}, P_{b_{-i}}) = P_{b_i} r_{CEV_{b_i}} \sum_{j \in NC_s} \delta_j \tag{17}$$

where P_{b_i} is the energy requested by car buyer i and $P_{b_{-i}}$is the vector of energy need for all buyers other than i.

The main objective of the CEV buyers is to minimize the sum of utilities for individual CEV buyers and the objective function can be written as follows:

$$\min_{r_{CEV_{b_i}}, i \in \mathrm{NC}_b} \left(\sum_{i \in \mathrm{NC}_b} \varphi_j(P_{b_i}, P_{b_{-j}}) \right)$$

$$= \min_{r_{CEV_{b_i}}, i \in \mathrm{NC}_b} \left(\sum_{i \in \mathrm{NC}_b} P_{b_i} r_{CEV_{b_i}} \sum_{j \in NC_s} \delta_j \right)$$

Subject to : $r_{CEV_{b_{\min}}} \leq r_{CEV_{b_i}} \leq r_{CEV_{b_{\max}}}$ and

$$P_{b_i} = P_{b_i} \sum_{j \in NC_s} \delta_j \tag{18}$$

where $r_{CEV_{b_{\min}}}$ and $r_{CEV_{b_{\max}}}$ are the minimum and the maximum buying rate fixed by the car buyers in the beginning.

As the selling/buying actions of one CEV influence all the others (CEV buyers and sellers) and as the bidding and auctions process depend on the strategy of all participants, we adopt a game theory to resolve (1)–(12).

Algorithm HLProfitX: Auction Model Based GT and ML.

Input: $NC_b, NC_s, r_{fg}, P_b, P_s, \sigma(0), \gamma, R(1), L(1), PM(1),$
$\beta, R_{max}, L_{max}, step$

Output: Best CEV buyers selected /* selected buyers */

1. CEV sellers calculate their r_{CEV_s} according to (7)–(11)

2. CEV sellers declare their range of tariff r_{CEV_s}
$r_{fg} \leq r_{CEV_{s_{\min}}} \leq r_{CEV_s} \leq r_{CEV_{s_{\max}}}$

3. **Each** CEV buyer :
1) calculate their r_{CEV_b} according to (7)–(11),
2) Calculate their utility φ according to (17),
3) Determine optimized r_{CEV_b} minimizing the electricity cost according to 18,
4) Send (r_{CEV_b}, P_b) to CEV sellers.

4. **Each** CEV seller:
1) Calculate their utility ψ according to (14),
2) Select the best CEV buyers according to eq. (15).

5. **If** no best buyer
CEV buyers increase target price $r_{t\,\mathrm{arg}}$ using (11)–(12),
Goto **1**

6. **Else**

7. Start payment process

8. Start energy transfer

9. **End**

The game equation related to the problem described by (13)–(18) can be written as follows:

$$\Phi = \{(NC_s \cup NC_b), P_s, \psi_j, P_b, \varphi_i\} \tag{19}$$

where the vector P_s represents the strategy of all CEV sellers and the vectorP_b represents the strategy of all buyers during the bidding process.

The solution to this problem is a Stackelberg Equilibrium [12].

We propose the algorithm HLProfitX for our auction model based on ML and game theory.

From the description of our proposed HLProfitX, we can see that the complexity is in the order of $O(NC_b * NC_S)$, where NC_b and NC_s are respectively the number of CEV buyers and CEV sellers in our system.

V. Performance Evaluation

In this section, we present the simulation results and discussions of the proposed scheme performance.

We consider a scenario in a real urban area of Ottawa where 20 parking lots are sharing a 4 × 4 km^2 (see Fig. 5). Table III summarizes the simulation parameters used in this section.

A. Assumptions for the Simulation

1) We suppose that CEVs can communicate wirelessly between each other's and each CEV determines the quantity of electricity sold or purchased during a period of time.

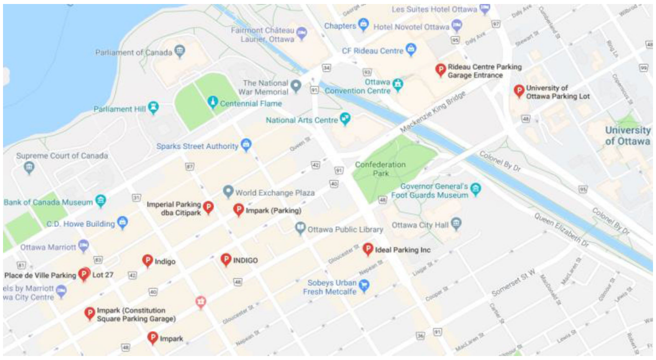

Fig. 5. Parking lots distribution in real map of Ottawa.

TABLE III
SIMULATION PARAMETERS

Parameter	Value
Electricity Price (based electricity requested level)	15 c/kWh [5]
Minimum Electricity Selling Price (Bidding based on game theory)	8 c/kWh (ToU)
Maximum Electricity Selling Price (Bidding based on game theory)	18 c/kWh [5]
Number of CEV buyers N_b	10, 30, 60
Number CEV sellers N_s	10, 30, 60
Energy requested by CEV buyers P_b	Uniform distributed between 20-75 %
Energy to sell by CEV sellers P_s	Uniform distributed between 20- 75 %
λ	Uniform distributed between 5-20%
δ	Uniform distributed between 10-20%
r_{fg}	ToU (Ontario)
D_{ch}, D_{Disch}	60 kW DC [16,17,18]
Charging time Max	20 min
SoC	Uniform distribution between 20-100%
EV Battery capacity	24 kWh [5, 17]
SoC_{BDT}	20%
β	Uniform distribution between 10- 50%
γ	Uniform distribution between 20- 80%
PM	Uniform distribution between 5- 35%

2) We suppose that all parking areas are equipped by an activated blockchain server.
3) All information related to CEV buyers or sellers profile can be communicated to the blockchain server.
4) We suppose that an efficient communication network system with secure privacy preservation mechanism is used to link all participants in the trading system. As a result, we consider that there is no problem with CEV's privacy in this article.

We conduct 1000 runs of simulation and we use Monte Carlo technique to extract the average values for each setting. We use MATLAB and Solidity [39] to perform the simulations. To prove the performance of our proposed scheme, we study: 1) the average CEV utility comparison between our proposed HLProfitX with our proposed AMERI and PETCON [22] for the same electricity quantity provided by CEV sellers and 2) the average buying and selling price using our proposed HLProfitX and PETCON [22] when the regulated electricity price (Smart Grid) is varying.

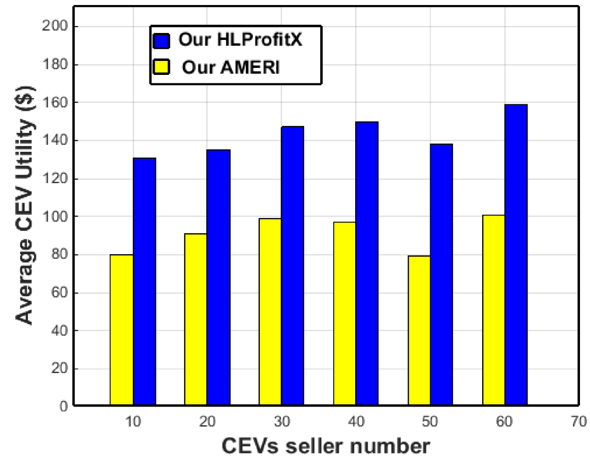

Fig. 6. Average CEV utility variation using our AMERI and HLPROFITX.

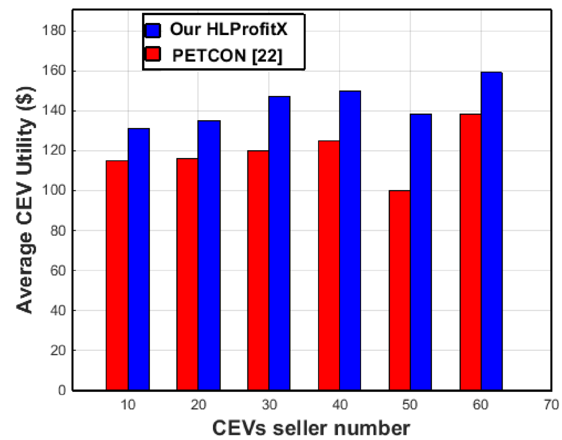

Fig. 7. Average CEV utility variation using our HLProfitX and PETCON [22].

Fig. 6 compares our HLProfitX (represented by blue color) and the AMERI (highlighted by yellow color). From Fig. 6 it is clear that, in terms of maximizing the trading of the electricity provided by CEV sellers, the HLProfitX algorithm outperforms the AMERI one and it makes trading electricity smartly more effective. This result can be explained by the fact that in HLProfitX algorithm all CEVs (sellers and buyers) participate in the trading electricity procedure which is based on the game theory. Also, they have the same chance to be selected as the winner without any privilege granted to anyone regarding its profile (power needed or sold and its proposed price) compared to AMERI one where CEV buyers are ranked and selected according to their electricity needs.

To prove the performance of our proposed scheme, we study the behavior of our HLProfitX algorithm compared to the PETCON [22] in terms of maximizing the trading of the electricity provided by CEV sellers. For this issue, Fig. 7 compares our

TABLE IV
AVERAGE CEV UTILITY COMPARISON BETWEEN OUR HLPROFITX AND PETCON [22]

	HLProfitX	PETCON [22]	Increasing rate
Average CEV utility	144	119	**21%**

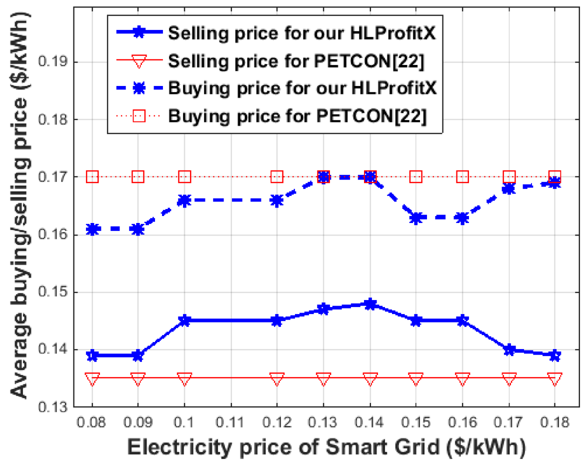

Fig. 8. Average buying/selling price variation using our HLProfitX and PETCON [22].

HLProfitX (represented by blue color) and PETCON (highlighted by red color). It is clear that our HLProfitX outperforms the PETCON one. This result proves the effectiveness of our proposed HLProfitX algorithm. It can be explained by the fact that our HLProfitX is based on ML model, which allows CEVs to learn from the current electricity market environment before announcing their bidding price. Also, our HLProfitX scheme uses game theory technique for the bidding process between CEVs while PETCON uses double auction mechanism to maximize the selling price without any consideration of the market situation. Our HLProfitX maximizes the trading quantity of electricity between CEV sellers and CEV buyers in the same time. It gives better management of the quantity of the electricity sold by CEV sellers.

Table IV presents the observation results obtained from Fig. 7, which illustrates the performance of our HLProfitX in term of the CEV utility. As shown in Table II, it is clear that our HLProfitX improves the trading of the electricity provided by CEV sellers and buyers with a saving rate of 21%.

We simulate now the average buying and selling price variation. Fig. 8 compares our proposed HLProfitX (represented by blue color) and PETCON (highlighted by red color). It is clear that our HLProfitX outperforms the PETCON one.

Our HLProfitX maximizes the profitability for the CEV sellers and CEV buyer in a better way compared to PETCON one (selling price is high; the buying price is low). PETCON gives lower revenue for CEV sellers and high cost for the charging process to the CEV buyers compared to our HLProfitX. From Table V, we can see that these results prove that our HLProfitX increases CEV seller revenues with 5.5% and helps them to set an optimal selling price and gives more satisfaction level to CEV buyers by lowering the electricity price by 3%. To conclude, our HLProfitX outperforms the PETCON in terms of improving the profitability for CEVs (buyers and sellers).

TABLE V
AVERAGE BUYING/SELLING PRICE COMPARISON BETWEEN OUR HLPROFITX AND PETCON [22]

	HLProfitX	PETCON [22]	Saving / increasing rate
Average buying price	0.165	0.17	**3 %**
Average selling price	0.143	0.135	**5.5%**

VI. CONCLUSION

In this article, an advanced DETF between CEVs in parking lots based on consortium blockchain, ML, and GT model was proposed. We design a distributed smart contract solution based on stochastic bidding process, which helps CEVs to sell and buy electricity with their maximum of profitability. We conducted numerical simulations with MATLAB and Solidity, and compared our proposed HLProfitX algorithm to PETCON [22] and the effectiveness of our proposed solution was proved.

As a future works, we plan to extend this article and we propose to study our scheme in large scale with realistic testbed considering renewable electricity integration with microgrid architecture. Also, the open electricity market with multicharging service constraints could be included with possible incentives for EV buyer and seller to participate in grid stability process.

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