Smart grids are able to provide optimal energy trading with demand responses via the use of cloud computing enabled virtual power plants.

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ABSTRACT

The growing penetration of energy from renewable sources and electric vehicles (EVs) presents a substantial challenge for something like the operator of the power grid in the form of an increase in peak demand as well as a loss in power quality. In addition, there is an increasing need for services that provide fast charging in smart grids. It might be difficult to keep up with the ever-increasing demand for quick charging services. In order to overcome this obstacle, we present in this article a new data mining architecture for managing virtual power plants (VPPs) in smart grids that is founded on cloud computing and combines commodities trading with services provision. This architecture is designed to manage virtual nuclear reactors. By buying electricity via an online energy trading platform hosted in the cloud, the planned system would enable electric vehicles (EVs) to be fueled at increased power rates without having an impact on the functioning of the power grid.

In addition, customers that own storage devices have the ability to sell any excess energy they produce to the market. The energy trading platform may, on the one hand, be seen of as a domestic market that is part of the VPP and is designed to increase that organization's income. On the other hand, it is in the owners of electric vehicles (EVs) best interest to keep the cost of charging as low as possible. Because of this, we represent the interactions that take place seen between EV owners and the VPP as a competitive game rather than a cooperative one.

In order to find the Nash equilibrium (NE) of the game, we first need to create an algorithm and then investigate the amount of computation and communication overhead it entails. In order to test the effectiveness of the proposed algorithm, we make use of actual data provided by the California Independent System Operator (CAISO). According to the findings of our research, users who own merely storage devices have the potential to receive an average income increase of approximately 200% by participating in the suggested single market. In addition, customers who use just electric vehicles may cut their charging expenses by roughly half, on average. Consumers that own electric vehicles as well as storage devices are able to cut their charging expenses even lower, by about 120%; in this scenario, users make a profit by making advantage of the single market.

I. INTRODUCTION

The rising contribution of renewable energy resources in the distribution grid is being driven in large part by the environmental advantages and economic incentives provided by these resources. New challenges to the reliable and stable operations of the power grid, particularly during peak hours, have been introduced as a result of the uncertainties associated with the production of green sources, the substantial increase in the capacity of

electric vehicles (EVs) in recent years [1, and the increasing interest in leveraging energy storage devices [2].

Several works have been written on the issue of charging electric vehicles using renewable energy in an effort to find a solution to this difficulty. In [3], electric vehicles were separated into several groups depending to the ways in which they charged in order to assign them distinct charging rates. This was done in order to account for the unpredictability that is connected with the production of renewable energy. In the study referenced in [4], a Markov decision process (MDP) was used in smart grids in order to tackle the issue of electric vehicle (EV) charging within the context of renewable energy aided charging. The authors of [5] tackled the issue of dealing with the unpredictability that comes with the production of renewable energy for both the power flow dispatch and charge management difficulties. At [6], the topic of charging maintenance in a charging station was presented in the form of a stochastic optimization problem. The authors of [7] designed an optimal charging strategy by making use of a stochastic game. This strategy took into account the dynamic behaviour of EV owners, which can lead to changes in charging parameters such as electricity generation or leaving time, while also incorporating renewable energy resources for charging. In [8], the behaviours of electric vehicle (EV) owners as well as the behaviours of charging stations were concurrently taken into consideration using fuzzy theory.

Because these charging stations employ alternating current (AC) chargers, the charging rates in [3], [4], [5], [6], [7], and [8] are restricted. Since AC chargers have a rather slow charging rate in comparison to other types, the amount of time required to fully charge an electric vehicle might be quite lengthy. Because it was anticipated that EV owners charge their vehicles at locations where they spend a significant amount of time throughout the day, such as their homes or places of employment, the previous research found that EV owners were content with the amount of time it took to charge their vehicles.

When electric vehicle owners are only in one location for a short period of time, as at a rest stop or a shopping complex, slow charging is impractical. CHAdeMO and Tesla superchargers are two examples of direct current (DC) chargers that are meant to enable high charging rates for owners of electric vehicles. Additionally, in order to increase the range of charging capabilities offered by conventional AC chargers, the combined charging system, or CCS, was created. These kinds of technologies may save the amount of time needed for charging by a substantial amount. In order to provide quick charging service, the chargers demand a very high peak power for only a very short period of time. This presents a technical difficulty for the operator of the distribution system (DSO). In previous research, the issue of how to provide DC charging services in smart grids without having to purchase a significant quantity of power from an external energy market was not addressed. This is a challenge that has to be solved. In this research, we present a cloud-based demand response mechanism for a virtual power plant (VPP) in smart grids in order to handle the relevant issues and include such concerns. In other words, the VPP is equipped with storage devices and generates energy from renewable sources. After that, the VPP will be able to run an energy brokerage account, which will result in the formation of an internal market that is hosted in the cloud. Through

the use of the platform, users who own storage devices have the ability to sell any excess energy to the VPP. At the same time, owners of electric vehicles (EVs) may buy energy via the platform, and after that, EVs can be charged at high rates by making use of the energy that is generated and stored by the VPP's renewable energy generating and storage devices. Because the price on the trading platform is lower than the price on the external market, the amount of energy that must be used in order to charge electric vehicles from the external market may be lowered thanks to the implementation of internal demand response management.

Previous research that has been done on demand response has often focused on making use of electricity price signals as the primary interaction parameter between power grid operators and end users [9], [10], [11], [12], and [13]. For example, in [9], the interactions were represented as a Dynamic stochastic general game in order to determine which methods would be most beneficial for end users as well as for those who operate electricity grids. There have been suggestions made in [14], [15], and [16] for ways to cut down on the peak energy use of the data centre. [10] took into account the unpredictability associated with the production of electricity from renewable sources. The authors of [11] proposed a reinforcement learning (RL) based solution for scheduling the consumption of appliances in the household and protecting the privacy at the same time. This was done in order to address the privacy concerns of end users and incorporate them into the demand response management structure. Recent advances in RL have been further utilised to implement demand response by scheduling the consumption of the heating, ventilation, and air conditioning (HVAC) system in the home as well as appliances in the building [12], [13], respectively. In [17], [18], and [19] there was discussion on using demand response in conjunction with VPPs in order to take part in the energy market. The idea of conditional value at risk was presented in reference number 17 as a solution to the problem of uncertainty linked with the generation of renewable energy. In order to engage in the energy market and put demand response into action, a multi-time-scale scheduling method that was presented in [18] was adopted. In [19], an issue that was investigated in [18] was also studied in [19]. In [19], an iterative method was developed to solve the defined issue. This was accomplished by decomposing the initial problem into a master problem and a subproblem before using the algorithm.

Recent publications [20], [21], [22], [23], [24], and [25] have brought considerable attention to the concept of peer-to-peer (P2P) energy trading. To simulate the interaction that takes place between producers and consumers on the energy trading platform, [20] presented a competitive game with no element of cooperation. In [21], a strategy that was based on the contract matching theory was used to discover the ideal quantity of power generation as well as the price of energy that should go along with it. In [22], a dependable method was suggested to rectify the mistake in the prediction of the development of renewable energy sources for the purpose of energy trading. The authors of [23] developed a bidding technique that was optimum by taking into consideration the amount of pain as well as the potential economic losses.

Energy trading using storage devices that are shared was suggested in [24]. The idea behind this is that end users may book a portion of the capacity of the shared backup system to save money on the

expense of installing storage devices in their own homes. A Stackelberg game was used as a model for analysing the interactions that took place between the end users, the power grid operator, and the shared storage system. The authors of the paper [25] constructed an algorithm with a two-time scale in order to tackle the issue of P2P energy trading. In addition, blockchain technology was used in order to prevent the data from being seen by outside observers of the energy market. In this article, we present a computational architecture for the VPP in smart grids that is based on cloud applications. This architecture allows for the implementation of energy trading as well as the provision of quick charging services. Demand response might be further realised with the help of this computational architecture. The design is comparable to those described in [26] and [27], in which users compete to acquire computing resources; however, in the infrastructure that we have presented, users compete to acquire energy. To be more specific, the VPP is responsible for controlling DC chargers [28, 29] so that the rapid charging service may be provided. It is possible for the chargers to be powered by a mix of the power grid, sources of renewables, and storage devices; this will lower the amount of electricity that must be purchased from the external energy market. In addition, the VPP manages a cloud-based trading platform for energy, which helps to create an internal market in which owners of electric vehicles may acquire energy. Because the money generated from selling energy in the internal market is larger than the revenue generated from selling energy in the external market, users who own storage devices are eager to sell excess energy in the internal market. The price of energy on the energy trading platform will be cheaper than the price of energy on the external market, which means that owners of electric vehicles will be ready to utilise energy from the energy e - commerce platform. Therefore, in order to provide the DC charging service, the VPP will need to make fewer purchases of electricity from the external energy market. The external demand for charging electric vehicles (EVs) is lowered, and as a result, this is the method by which demand response may be implemented in smart grids. In contrast to [30] and [31], which focused on identifying the best possible places for the fast-charging service, the primary objective of this study is to develop a system that is capable of providing the fast charging service without interfering with the functioning of the power grid. EV owners will be able to access rapid charging services from the VPP under the framework that has been suggested, and the VPP will be able to alleviate congestion for the DSO by dispatching energy that has been collected from energy trading users.

Our primary contributions to this effort may be broken down into three categories:

Researchers suggest a framework platform mathematical architecture for the VPP that operates an internal market for implementing demand response. This will enable users to sell any excess energy they have on the internal market, and at the same time, electric vehicles will be able to receive a high charging rate.

In order to find the non-cooperative game's Nash equilibrium (NE), which simulates the interactions between EV owners and the VPP, we construct techniques to search for it. In addition to this, the computational complexity, the communication overhead, and the performance of the algorithms are all assessed.

We investigate how well our algorithm's function using actual data obtained from the California Independent System Operator (CAISO). According to the findings, users who have storage devices have the potential to greatly increase their earnings by taking part in the planned internal market, while users who merely have electric vehicles have the potential to significantly cut the cost of charging their vehicles.

The remaining parts of this work are structured as described below. Section 2 is where we get things off by presenting the system model. The interactions between the users and the VPP are modelled as a competitive game in Section 3, after which the section is named. In Section 4, we offer the design of methods that may be used to locate the NE of the game.

Next, the legitimate database that will be used to assess the suggested approach is presented in Section 5, along with the findings of the evaluation itself. The findings are presented in section 6, along with some recommendations for further investigation.

II. SYSTEM MODEL

We provide a unique architecture that is based on cloud applications and it is used by the VPP in distributed generation to just provide services for energy trading and charging. We will suppose that the distribution grid has a total of N users, each of whom falls into one of three categories: type 1, type 2, or type 3 users. The rules about how energy can be traded can be seen as an internal market for customers.

Let's say that sets N 1, N 2, and N 3 represent the users who fall into categories type 1, type 2, and type 3, respectively. Within the internal market, type-1 users sell whatever excess energy they have to a trading platform that deals in energy. Both type-2 and type-3 users buy energy via the trading platform. However, type-3 users have the additional option of buying energy from the VPP by selling the energy that is currently stored in their storage devices. The grid for distribution is broken up into M different sections. Aj is the abbreviation for the group of users who are located in the region j 2 f1; 2;... Mg. In addition to this, Ut is a representation of the group of type-2 and type-3 users operating in the internal market in the period t. The cost of acquiring one unit of energy from an external energy market at a certain point in time is symbolised by the symbol kt in this context. When taking into consideration the government's programme that provides monetary incentives to end users in order to promote sustainable power, it is tried to be introduced as the unit price from the international setting backed by the government in order for users to sell their abundance of resources to the international setting. This is done in light of the fact that the government has this policy.

Type-1 User

In our hypothetical situation, each type-1 user has merely a storage device and some kind of renewable energy generator, such as solar power. Through the energy trading platform that is run by the VPP, type-1 users are given the opportunity to sell any excess energy that is contained inside their storage devices at time t. The ith user in N 1 provides aET i;t units of energy from their own storage device at a price per unit that is equal to bET i;t. The VPP will answer with a variable bi;t that indicates the percentage of the user's energy that will need to be purchased. The amount of energy stored in the devices belonging to user I I 2 N 1) at time t is zi. Users of Types 2 and 3 respectively. Users of types 2 and 3 both have electric vehicles, and they are interested in acquiring charging services from the VPP. The customers who fall into type 2 do not have any renewable energy generating or storage equipment, in contrast to the consumers who fall into

type 3, who have This is the primary distinction between the two groups of users. The amount of energy that is now stored in the device belonging to user l (l 2 N 3) is denoted by the symbol zl;t.
The moment that user l (l 2 N 2 [N 3) first enters the internal market is denoted by the numeral al, and the time that user l exits the internal market is denoted by the numeral fl. We provide each EV with the same index that is associated with its user. el;t is a notation that stands for the energy level of EV l at time t. Therefore, the demand for EV l at time t is equal to the maximum energy level of EL at that moment, which is denoted by dl;t 14 emax l el;t. The owners of EVs will then send a price, denoted by bEV l;t, and an amount of energy, denoted by aEV l;t, to the VPP at time t. These values will represent the price and/or the number of calories that the user would like to pay in order to use the charging service provided by the VPP via the energy trading platform that is hosted in the cloud. Additionally, the VPP enables the user to l 2 N 3 transmit sEV l;t to acquire energy by exchanging the energy stored in the storage device with the VPP so that they may participate in the internal market. After

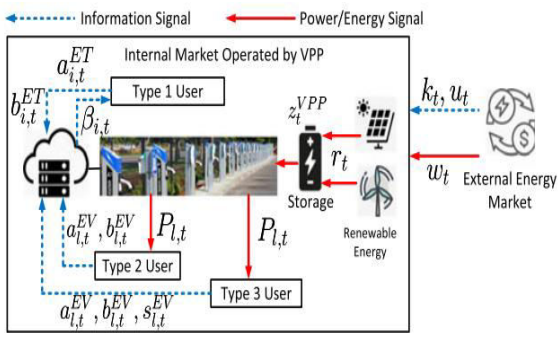

Fig. 1. The model of the system that was utilised for this work

putting into action the strategy for trading energy, the total amount of power that EV l gets from the VPP at time t is

$$P_{l,t} = P_{l,t}^{Grid} + P_{l,t}^{ET} + E_{l,t}^{ST}/\tau, \quad (1)$$

where P Grid l;t refers to the electricity coming from the power grid and P ET l;t refers to the energy trading platform, respectively. The amount of energy that may be obtained for charging electric vehicles by exchanging the energy contained in storage devices with the VPP is denoted by the notation EST l;t, where t refers to the length of time that a time slot occupies. EST l;t will always be set to 0 while l 2 N 2 is present since type-2 people do not have storage devices in their homes. P max l and P min l are the notations that are used to indicate the upper limit and lower bound of Pl;t, respectively. Following the receipt of electricity, the electric vehicle's current energy level is calculated by

$$e_{l,t+1} = e_{l,t} + \eta_l P_{l,t}\tau, \quad (2)$$

where hl represents the charging efficiency of EV l and user l 2 N 3 updates the metabolic rate of something like the storage devices by

$$z_{l,t+1} = z_{l,t} + g_{l,t}\tau - E_{l,t}^{ST}, \quad (3)$$

where glt represents the amount of renewable electricity that user l generated at the given time.

III. PERFORMANCE COMPARISON

The amount of money made by using the suggested approach in comparison to the algorithms described in [39] and [21].

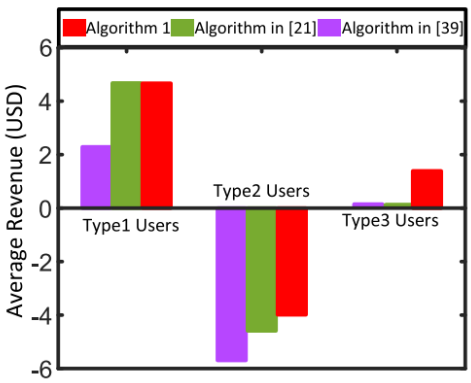

Figure 5 shows the revenue generated by users in the various algorithms.

the type-3 users are not shown, and as a result, the income generated by type-3 users is assumed to be zero. The trading of energy is taken into consideration in this article as well as in [21], and the income on the energy e - commerce platform is more than the cost of selling energy than by selling it to other parties on the open market. Because of this, The income generated by type-1 customers in [39] is about 51% lower than for those users who identify as type-1 in the proposed method and in [21]. The type-1 users then decided to keep the same pricing across all of the simulations in order to ensure that type-1 consumers get the same amount of income from both the proposed approach and [21]. The users of type-2 are shown to get in [39]. the greatest possible billing cost, which is about 43 percent more than for approach being suggested here. This is due to the fact that owners of EVs pay the same price for power as that of the external market in order to use charging electric vehicles need energy from both the exterior market and the storage devices included inside the VPP. The cost of the power may be brought down by increasing participation in the domestic market for those with type 1 diabetes. Therefore, the suggested approach results in less power price due to the increased demand posed by type-2 customers in [21]. energy purchased from a third party market. Therefore, those who have type 2 diabetes still spend around 15% more than what was planned in [21]. If owners of electric vehicles also have equipment for the generation and storage of renewable energy, the cost of the electricity used to power the vehicles may be reduced even more. diminished, as shown by the users of type-3. The quantity of power that was bought from outside sources in its entirety is determined by the letter P tð P l P Grid

l;t t þ wtÞ. The algorithm described in [39]. [39] has all the information pertaining to the future, such as the price of power, the generation of renewable energy, and the base load profile, so that it may find the best quantity of energy that should be bought from a market that is outside the company. Only the procedure that was suggested gets the price of the power for the future W time periods that resulted in an approximately 6% increase in the quantity of energy being purchased than [39]. On the other hand, the VPP in [39] manages to meet the minimal profit since it does not run an internal market that is designed to generate profits, and it is required to acquire energy from the charge their storage devices, they must purchase power from an external market. The algorithm in [21] makes purchases that are around 90% greater in quantity. energy purchased on the open market in contrast to the one that was suggested. method and [39]. Electric vehicles get their power from this kind of energy. the minimal energy that has been established, P min lt, to charge electric vehicles.

IV. CONCLUSION

We proposed a brand-new structure for an economic area that is based on cloud computing and is operated by the VPP in smart grids with three groups of users. This framework is designed in such a way that users can sell energy surplus they have stored in their flash memory to the market, while users who have electric vehicles can purchase energy to charge their EVs. We characterised the interactions that take place between the VPP and its users as competitive games and developed an algorithm in order to locate the Nash equilibrium of the games. In addition to this, we investigated how well the suggested method worked. We validated our suggested algorithm by using data from the California Independent System Operator (CAISO), and we reviewed its effectiveness in terms of the income of the VPP and the revenues of the customers. According to the findings, consumers have the potential to generate roughly 200% more money compared to when they were simply selling energy to the external market. In the same vein, consumers who own electric vehicles have the ability to dramatically cut their charging expenses by increasing their charging rates, all without negatively impacting the functioning of the power grid. Because of this, with the help of the suggested framework, a strategy that is beneficial to both users and the VPP in smart grids was developed. The current information, which includes the states of the storage devices and the generation of renewable energy, serves as the basis for the choices of the users within the framework that has been offered to sell any energy excess to the internal market. If the users are able to improve their ability to learn and make accurate predictions, there is a possibility that their earnings may increase. To be more specific, techniques of machine learning may be used to anticipate the characteristics of the environment and establish the most effective bidding tactics for the users. The VPP is responsible for ensuring that users who are selling excess energy to the internal market have obtained the appropriate quantity of energy in their storage devices before they can participate in the energy trading. However, because of concerns about users' privacy, the VPP is unable to have direct access to the computer devices used by users. One way to reach this goal is to use proofs from the field of cryptography that aren't very strong.

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