

# We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

4,800

Open access books available

122,000

International authors and editors

135M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index  
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?  
Contact [book.department@intechopen.com](mailto:book.department@intechopen.com)

Numbers displayed above are based on latest data collected.  
For more information visit [www.intechopen.com](http://www.intechopen.com)



---

## V2G Services for Renewable Integration

---

Mahmoud Ghofrani, Eric Detert,  
Negar Niromand Hosseini, Amirsaman Arabali,  
Nicholas Myers and Phasith Ngin

Additional information is available at the end of the chapter

<http://dx.doi.org/10.5772/64433>

---

### Abstract

With the proliferation of renewable energy sources (RES) and the growing consumer demand for plug-in hybrid (PHEV) and total electric vehicles (EV), the limitations of the aging electrical grid distribution infrastructure is becoming more and more apparent. The development of better infrastructure, therefore, is at the forefront of research. The development of a smart grid, a bidirectional distribution infrastructure, will allow for two-way “communication” of power distributors and aggregators with multiple smart platforms, such as smart buildings, homes, and vehicles. The focus of this chapter is to outline the means of (electrical) vehicle to (smart) grid (V2G) interactions and how attaining a synergistic relationship is vital to improving the way power is distributed. The ability of fleets of EVs to act as a unit for excess power storage allows for the increased integration of RES into existing grid infrastructure and smart grids in the future through the bidirectional communication; providing support, giving back stored power into the grid to lessen the load felt by generation utilities, augment stochastic RES when generation is not meeting demands, lowering costs for both sellers and buyers, and above all, working toward the betterment of Earth.

**Keywords:** electric vehicles, renewable energy, vehicle-to-grid, optimization, smart grid

---

## 1. Introduction

The world is presently facing many energy problems. Fossil fuels have been the main dominant energy source for both the transportation sector and power generation industry even if this energy source produces greenhouse gases (GHGs) which have a negative impact on climate

---

change [1]. With fossil fuel prices increasing and its negative environmental impact, oil is becoming less of a long-term energy solution, and more renewable sources of energy are being sought. Wind and photovoltaic solar are renewable energy (RE) sources that are rapidly replacing conventional power sources. On the other hand, electric vehicles (EVs) are becoming more and more popular due to the fewer emission and low oil dependency.

The electrical vehicle is a zero emission vehicle because it does not produce the pollution associated with internal combustion engines (ICEs). However, the charging through fossil-fuelled electrical generation still makes an environment impact since most electricity is generated by burning fossil fuels. But comparing with cars operated by gas power, cars operated by batteries are cleaner because they produce less carbon emissions. Moreover, battery-powered motors cost less to operate. The other advantage of EVs is safety and efficiency. EVs use the advance technology to maintain the vehicle adequately and to keep the right supplies on hand in case of emergencies. EVs offer benefits to the transportation sector and the electric power system. They help strengthen the economy, are more environmentally friendly, and can reduce strain on the petroleum industry by using renewable generation, especially photovoltaic solar and wind, which is an important part of the transition to cleaner sources of power. EVs are the best option for greener and economic driving [2].

An electric vehicle (EV) is considered an electrical drive vehicle which uses one or more electrical motors or traction motor for propulsion. An EV is powered through a collector system by electricity from a self-contained battery or generator to convert fuel to electricity. These are termed battery electric vehicles (BEVs), or if powered with an off vehicle source, termed plug-in hybrid electric vehicles (PHEVs) [3].

The battery electric vehicle is one type of electrical vehicle that uses chemical energy stored in rechargeable battery packs. There are three major parts in the typical architecture of BEVs: electric motor, rechargeable battery, and controller. The electric motor uses a rechargeable battery as an energy source to generate propulsion. The controller manages the power supplied to the electric motor. Another important part of a BEV is the inverter, which is for converting the electricity stored in the battery (DC) power to alternating current (AC) power [3]. The Nissan Leaf is a battery electric vehicle which relies on the grid to recharge its battery. Its battery packs can be charged from fully discharged to 80% capacity in about 30 minutes using DC fast charging. It does not produce pollution or GHGs, and also helps to reduce dependence on petroleum [4].

The plug-in hybrid electric vehicle is a hybrid electrical vehicle that can use rechargeable batteries or another energy storage device. They are usually equipped with both an electric motor and an additional internal combustion engine for propulsion. PHEVs can be driven in two modes: charge depleting (CD) and charge sustaining (CS). PHEVs produce energy from on-board battery packs when they operate in CD mode, and they switch to CS mode and utilize the ICE system for further propulsion if the charge of the battery has been depleted to a predetermined level. There are three categories of plug-in hybrid vehicle: parallel hybrid, series hybrid, and power-split hybrid. The parallel hybrid is the most commonly adopted. They use both electric motor and an engine to power the driven wheels in a car [3]. The Toyota Prius is a hybrid car with an internal combustion engine. Its large on-board battery recharges

while the gasoline-fuelled ICE is running. It is fully self-sufficient and does not rely on the grid. It can use its large on-board battery for 34–40 miles before the on-board gasoline generator kicks in. It is fully capable of making long trips, but can also go short distance powered entirely by the battery without any gasoline [5].

## 2. Vehicle to grid (V2G)

### 2.1. Concept

The advancement of EV technology has brought on additional attention into the integration of the transportation sector into the power grid. The control and management of EV loads by the power utility using the communication between vehicles and the power grid is referred to as vehicle to grid. Some other similar concepts are vehicle to home (V2H) and vehicle to vehicle (V2V). These involve exchanging power between an individual's home power network and their vehicle, or exchanging power within a community of electric vehicles [6].

Currently, the transportation sector is primarily using gasoline or petrol for propulsion, and does not have any interconnection capabilities with the power grid. However, with the advancing adoption of EV into the transportation market, the idea of allowing EVs to plug into the power grid, to not only charge their vehicles, but also discharge energy back into the grid, becomes more practical [2].

The V2G concept could provide many services to power grid but presents some challenges as well. The benefits of such a system include peak load shaving, load leveling, and voltage regulation, which will ultimately result in maximizing profits. The challenges include the logistics of retrofitting the current infrastructures and gaining the support of the public and policy makers.

One issue includes the accelerated battery degradation due to increasing the charging cycles of each vehicle's battery. Studies are being conducted to collect more accurate data on battery lifecycles. These studies will provide more information so that policy makers can either prevent consumers' battery degradation, or more accurately consider the cost of that wear and implement that into the pricing scheme. The battery degradation scenario is part of the social barrier that V2G may present. Skeptical EV owners may wonder how they can be assured they will have enough energy stored in their vehicle to accommodate their transportation needs. There are also concerns of how the consumers will be fairly compensated for discharging their energy back into the grid.

The challenge of retrofitting the power grid infrastructure could be the biggest hurdle. Implementing V2G would be a large investment. Improving hardware and software in the grid system would be one major cost. Another would be adding a bidirectional battery charger to each EV. Bidirectional chargers consist of a complex controller and high tension cabling with stringent safety requirements. V2G implementation would mean frequent charge and discharge cycles resulting in more losses from energy conversions. A large fleet of EV's charging and discharging would add up to large energy losses for the power system [6].

The overall concept of V2G began with the idea of tapping into the underutilized power capacity of the passenger vehicle fleet. Whether it is internal combustion or all electric, the vehicle fleet in the United States has much more energy capacity than all the U.S. electrical generating plants combined and they sit idle nearly 95% of the day. As the automobile industry begins to shift more toward electric and hybrid vehicle production, the utilities have begun to consider using these vehicle batteries as a storage cell. Studies have shown that even with unfavorable assumptions about cost and lifecycles of batteries, over a wide range of conditions, the value to the utility of tapping vehicle electrical storage exceeds the cost of a two-way hook-up and reduced battery life. It has been considered to offer incentives to the vehicle owner as a purchase subsidy, lower electric rates, or purchase and maintenance of successive vehicle batteries [7].

A possible configuration for an EV participating in V2G technologies would have a user interface with the vehicle allowing the owner to disable or limit the discharge to the grid. An intelligent charge controller could have several options for the owner to charge and discharge the vehicle. Some options could be to charge now or charge when cheap, or to set a minimum threshold to maintain enough charge for the owner to be able to cover a particular driving distance. This would allow for more flexibility for owners to participate as much as their lifestyle allows. An incentive-based program would hopefully garner more favor from consumers [7].

## 2.2. Smart grid

A smart grid is a modernized electrical power grid that involves communication technology between the utility and the consumers using computer-based remote control and automation to improve reliability, efficiency, and sustainability of the power supply. Two-way communication between the utility and its customers by way of sensors and smart meters throughout the smart grid are used for real-time data acquisition. The data collected from these sensors and smart meters are then used by intelligent and autonomous monitoring control to supervise and optimize the overall operations of the interconnected components [2].

An additional characteristic that separates the smart grid from the conventional grid is that consumers can actively participate in the grid operation. The smart grid would contain advanced metering infrastructure that would allow for consumers to access the real-time information about electricity usage, tariff, and incentive information. They can use this information for their own gain by adjusting electricity usage patterns and preferences. These adjustments would likely help to balance out the overall energy supply and demand. The smart grid concept also incorporates a widely dispersed distribution of generation units from various forms of renewable generation and conventional power sources. This variety of generation sources will provide better overall reliability and reduce risks from attacks and natural disasters [2].

The ability to accommodate renewable energy sources more efficiently is another attractive characteristic of the smart grid. Wind and PV solar energy has unpredictable and intermittent supply of power to the grid. Due to varying weather conditions, the power produced from these sources can be much higher than the power demand in some cases and much lower in



other cases. They are variable with time and unable to dispatch on command. However, these sources are practically viable if able to store and later discharge excess energy. The promise of balancing the electricity generation from renewable sources with consumer load is realistic with energy storage systems and controllable dispatch loads. A smart grid that communicates supply and demand data will make renewable sources with energy storage systems a practical solution [1].

The smart grid can improve grid reliability and power quality but implementing it into existing infrastructure will be a challenge. In the meantime, there are several smart grid projects underway all over the world. According to the Global Smart Grid Federation Report, the leading projects are taking place in Australia; Ontario, Canada; London, Great Britain; Ireland; South Korea; and Houston, TX, in the United States [8].

### *2.2.1. Smart charging/discharging*

As EVs become more prevalent, a high concentration of vehicles charging over a small period of time will inevitably lead to overload conditions in local nodes of the grid. This could lead to interruptions and/or imbalances that would degrade the service quality, increase line losses, or damage equipment. Smart grids are fundamental in smart charging management strategies that can reduce peak load on the grid. This will also allow for the advantage of coordinating vehicle charging in order to store surplus grid energy at a given instant and inject it into the grid when needed [9].

The potentially undesirable effects of uncontrolled EV charging such as overloading the power system facility would lead to an unregulated, less efficient electrical supply. To alleviate this condition, some smart charging schemes have been developed to minimize charging costs. Some optimization algorithms have been developed to create a better solution for EV's charging and discharging into the grid. Some smart charging concepts include using day-ahead energy resource scheduling for smart grid by considering all the dispersed energy resources (i.e., wind, solar, conventional, etc.) and the V2G participants. An optimization approach could be used for intelligent optimal scheduling. To facilitate this intelligent charging concept, a radio frequency identification (RFID) tag technology would be used to ID those plugging into the grid. Some options could be considered where EV owners could control and monitor their charging through a mobile web application. Parameters could be adjusted such as the desired state of charge, arrival and departure times, or options for the V2G services to maximize profit. Other intelligent charging models use consumption historical statistics with data mining approaches. This method could include using the GPS function on an EV owners' mobile device to help determine driving characteristics [1].

Efforts have been made in developing smart charging strategies to account for the efficiency of the charging process. An effective dispatching strategy needs to account for the losses in the charging process to accurately estimate the amount of energy fed to the battery from the grid. Accounting for these nonideal conditions will allow for better overall system performance. Currently, the charging efficiency of batteries for electric transportation still is largely dependent on the charging rate due to the internal battery resistance. On a typical lithium-ion cell, the charging rate is normalized with respect to the battery capacity. The efficiency will

decrease significantly with the charging rate due to the internal battery resistance power dissipation with the charging current. These charging characteristics need to be taken into account to develop smart charging strategies [9].

### 2.2.2. *Advanced communication and control*

The critical portion of the smart grid is the communication and control aspect. A two-way communication network enables demand response technologies which can control distributed energy resources over dispersed geographical areas [1]. As smart grid capabilities increase with newer automation and communication networks, power utilities and aggregators are able to see real-time distribution and load demands on the network and, via the bidirectional communication, control and optimize the supply of power. A key benefit with EV is that they can act as energy storage units that interact with the smart grid, through “smart” charging stations. This dual-channel communication is only available through the use of bidirectional communication, not unilateral, which among other reasons makes the switch from non-EV to EV even more practical. These interactions can help optimize power distribution, decreasing degradation and increasing quality of deliverable power through active power support and reactive power compensation [2]. With an infrastructure of smart meters, the power system can obtain the information of power demand and consumption in the system to better schedule generation and distribution for locational pricing. With a large number of smart meters, fiber optics as a medium would not be feasible due to cost, and wireless communication would be the preferred method between smart meters and control centers [8]. The benefits of wireless include low cost infrastructure and wide area coverage [1]. Perhaps a hybrid wired/wireless system can be used in the future for security concerned consumers [10].

In comparison with traditional data networks, the smart meter network of a smart grid would have some unique challenges. One challenge would be the volume of traffic and limited bandwidth due to the large number of smart meters. Another would be the requirement for real-time data transmission. The power grid is a very dynamic system and it is critical to have current data. Delays in data transmission could result in instability to the power market. Another challenge would be taking the characteristics of the power systems into account for charge scheduling. Traditional scheduling algorithms that maximize the throughput or minimize the average delay may not be valid in a smart grid. Addressing these challenges could include introducing locational marginal pricing and a model of power load variation into a scheduling algorithm [10].

On the consumer side, there are several ideas on how EV owners can exercise control of their vehicle’s charging schedule while still allowing the power grid to benefit from the EV battery source. One idea would consider equipping each V2G compatible EV with a user interface device to allow the driver to receive instructions or seek advice for charging/discharging processes. An alert would be issued in the event when the EV’s battery capacity is below a predetermined threshold level. This alert can include near-by charging stations, distance, their energy price, etc. The alert can also provide the driver with instructions to bringing the vehicle to appropriate charging stations to serve as a backfill battery. All of this information exchange would be accomplished through wireless communication and hall-effect current sensors.

System architecture of a vehicle to grid communication system would possibly include several road side units that would communicate between passing vehicles, nearby charging stations, and the smart grid. The road side units would allow communication between vehicles and charging stations when the transmission ranges would not be sufficient. The data transfer would be triggered by the driver or a recommendation system. With a driver-triggered scenario, the driver checks the state of charge and seeks advice on charging through the user interface on board the EV. The communication module will send a message to the nearest road side unit to request information of near-by charging stations. The inquiry would generate a reply back to the vehicle with its geographical location and/or current energy price. The on-board controller would collect data through the message exchanges and start the recommendation system. This recommendation system would decide whether it is the right time to charge or not based on the vehicle's state of charge, energy prices, and grid status. It would either recommend to charge or defer to off-peak hours when energy rates would likely be lower.

With a system-triggered scenario, the recommendation of energy charging depends on factors such as the grid load, the state of charge of the vehicle, and real-time energy prices. The system would receive alarms from sensors on the vehicle (for battery capacity), and then send messages to the road side units to start a recommendation process [11].

### **3. V2G services for renewable energy (RE) integration**

V2G systems can provide a variety of services to power utilities, grid operators and aggregators, as well as the EV owner and even the environment. These services include ancillary services, time shifting, active power support, and reactive power compensation through voltage regulation. These services will become invaluable due to their mitigation of the increasing uncertainties and intermittencies of the grid due to the renewable energy integration [12, 13].

#### **3.1. Ancillary services: spinning reserve**

Ancillary service refers to the supporting service supplied to the power grid in order to improve upon and maintain the reliability and efficiency of the power grid, this also increases sustainability. There are several ancillary services that are required for the security, reliability, and stability of the grid. These services make up reactive supply, voltage control, regulation, operating spinning reserve, operating supplemental reserve, and restoring energy imbalance [14]. V2G technology inputs ancillary services to the power grid through a spinning reserve service, where the energy stored in the grid-connected EVs is utilized as an additional generation capacity to make up for the generation deficiencies due to generation outages [15]. The spinning reserve service provided by V2G technology provides a platform to initiate failure recovery, as well as reduce the backup generation capacity [16, 17].

#### **3.2. Time shifting**

In time shifting services, storage capabilities and technologies are required to necessitate and provide energy within a timeframe of 5–12 hours. In this particular case, energy storage



systems are required to absorb and assimilate all of the energy from RESs during off-peak demand periods. This absorbed energy may be supplemented with cheaper alternative power sources brought from the network if necessary, and then selling it during peak power demand periods; mitigating the activation or update of other conventional and more mainstream peak power generation plants [18].

### 3.3. Active power support

EV can provide numerous methods of active power support. Through bidirectional communication, the excessive EVs energy that would otherwise be wasted can be sent back to the utilities and aggregators via the smart grid through specialized charging stations, parking lots, etc. The goal of active power support is to ease the demand on the power utilities. The demand for power is not constant, in that demand ebbs and flows, with a decrease in the late nights and sizable demands during the mid-day and early mornings. This fluctuation degrades the generative power of utilities. In addition, utility customers see the prices of electricity change in accordance to the demands; having to pay a premium price for electricity usage during peak hours. Power systems are designed for worst-case conditions, that is, assuming maximum load and demand. It follows that whenever the demand is less than maximum, the systems are being underutilized. Operating at maximum capacity also wears out the system over its life time. EVs are able to provide two kinds of active power support, load leveling and peak shaving, to prolong power system longevity and lower the economic strain on consumers and EV owners [2].

#### 3.3.1. Load leveling

Load leveling is the goal to “spread out” the high demand curve during peak hours, thus decreasing the operational strain on the systems. EVs act, when on the V2G scale, as a collective distribution network to supply excess power back through the smart grid to level out the load peak. By using smarter distribution networks, the demand for sole generation and distribution felt by power utilities and aggregators is lessened, prolonging system life and mitigating unnecessary costs of repairs or upgrades. Utilizing the power systems at a level less than peak for a longer period of time will lead to less losses overall, prolonging usability and lowering overloading chances. Due to the stochastic nature of weather-dependent renewable resources, the output power is unreliable to constantly meet the load. Using distribution networks to store excess energy, like EVs, to act as a buffer to provide power whenever levels of renewable generation is not at demand will allow year-round operation of renewables through lowered reliance on perfect weather conditions [19].

#### 3.3.2. Peak shaving

By allowing the power systems to not operate at worst-case peak levels, the degradation of the systems is lessened and the overall life of the system and its generative abilities are increased. This allows for longer and higher quality power distribution. EV connected to the grid during peak hours increases the load at the low-voltage network. This increases the demand for current and consequently the need for power from the medium and high-voltage networks.

The increased load will force more current through transmission cables and transformers from high- and medium-voltage networks down to low-voltage networks, which in turn increases transmission losses and thermal wear on components, decreasing usability. By peak shaving, this load is lessened through coordinated EV charging and EV-based distribution networks through bidirectional infrastructure. The power delivered back to the utilities and aggregators through V2G will decrease the peak demand, the degradation of generation resources, distribution resources, and, by allowing the system to operate at a lower level, the premium price of electricity faced by EV owners during peak demand hours [19].

### **3.4. Reactive power compensation: voltage regulation**

A constant problem facing power utilities and aggregators is ensuring that the voltage and current distributed through the network are in phase. However, with each load attached, a disparity between the two can occur, resulting in a decrease in the deliverable power factor which requires corrective measures. Reactive power support is able to supply voltage and current to meet reactive load at the distribution level that would otherwise has to be supplied by generators. Without reactive power support, supply voltages would fall below minimum levels and more current would be needed to push through transmission lines, resulting in thermal wear and potential blackouts [20].

Specialized capacitor banks are used by utilities to locally supply reactive power at the load bus to lessen the load felt at the utility level. This specialized volt-ampere reactive (VAR) compensator banks are costly and difficult to upgrade. By using the DC-link capacitors present in EV chargers, utilities through the smart grid would be able to use the V2G distribution network as a reactive power support system in addition to active power support network via the bidirectional communication infrastructure. Since the DC-link capacitors supply the reactive power, no strain is placed on the EV battery [21].

## **4. Optimization of V2G services for RE integration**

### **4.1. Optimization techniques for V2G services**

Mathematical modeling of systems allows for variable change while trying to maintain a maximization or minimization of a criterion or many criteria. This modeling allows for experimental change without potential risks to the actual system. Finding an optimal middle ground between maximized efficiency and minimized cost is achievable through mathematical modeling using various optimization techniques and functions. The different techniques are summarized in the following sections.

#### *4.1.1. Classical optimization techniques*

Classical techniques are utilized when the optimization function is a continuous and/or differentiable function. The solutions of optimization are found using differential calculus. The most utilized types of classical models are: linear programming (LP), nonlinear programming

(NLP), dynamic programming (DP), mixed-integer programming (MIP), stochastic programming (SP), convex programming (CP), and analytical modeling (AM).

#### *4.1.2. Metaheuristic optimization techniques*

Metaheuristic optimization techniques find, generate, or select a heuristic in this case a method of searching for an optimization strategy that may provide the best solution to the optimization problem with nonderivative, noncontinuous objective functions. These metaheuristic methods sample from a much larger sample set to find a solution that best fits the entire set. It is based off of random operators to find the best solution to the set of variables faster than iterative or simple heuristics. The common types of metaheuristic techniques are: genetic algorithms (GA), particle-swarm optimization (PSO), ant colony optimization (ACO), simulated annealing (SA), and Tabu search [3].

#### *4.1.3. Hybrid optimization techniques*

Hybrid optimization techniques are techniques that combine two or more of the previously described methods, either classical or metaheuristic. Typically, they combine iterative approaches to heuristic solutions.

### **4.2. Optimization objectives**

The focus on optimization for V2G services are cost, efficiency, and emission optimization. Through the use of the optimization techniques listed above, significant gains can be made toward producing the most efficient and cost-effective EVs, maximizing V2G interactions, and improving smart grid technologies and power generation and distribution.

#### *4.2.1. Cost optimization*

Cost optimization is focused on minimizing the costs of interaction between EVs and RES providers through the smart grid. Providers wish to reduce costs and maximize profit while EV owners wish to minimize the cost of charging and vehicle maintenance [3].

##### *4.2.1.1. Operational cost minimization*

Operational costs and their minimization are crucial for all market participants including the generation, transmission, and distribution providers and users [3]. **Table 1** summarizes the related research works, their objective functions, techniques in use for optimization, and their main findings.

Reference	Objective function(s)	Optimization technique	Findings
[22]	$\min C_{Iso,T}^C = \sum_{i=1}^n C_i^d P_i^d v_i T + C_B^d P_B^d T + \sum_{k=1}^m C_k P_k z_k T$ $\max C_{Iso,T}^P = \sum_{i=1}^n (-C_i^C P_i^C) v_i T - C_B^C P_B^C T$ <p><math>C_{Iso,T}^C</math> is the islanded operating cost over a horizon of length <math>T</math>; <math>C_i^d, P_i^d</math> are the discharging price and power of the <math>i</math>th EV; <math>C_B^d, P_B^d</math> are the discharging price and power of battery swapping stations (BSS); <math>P_k, C_k</math> are the amount of load shedding of the <math>k</math>th interruptible load (IL) user and its service price; <math>v_i, z_k</math> are in binary with <math>v_i</math> being a 1 if the <math>i</math>th EV is connected to the microgrid after islanding while fixed to zero when the <math>i</math>th EV is not available; <math>z_k</math> is 1 when the interruption time of the <math>k</math>th IL does not exceed the longest time per interruption while it is enforced to be zero if the time limit on load shedding is violated.</p>	Classical (Mathematical programming)	On a regional level, a management strategy is proposed by this paper for minimizing costs and maximizing profits of an islanded microgrid with renewable resources. The strategy is beneficial for managing the load of EV fleets and optimizing the operation to mitigate the load impact by leveling and peak shaving. The strategy uses fuzzy systems to obtain the charging price EVs.
[23]	$\min TSC = \sum_T^{t=1} (u_{j,t}^{DG} P_{j,t}^{DG} B_{j,t}^{DG} + S_j^{DG}  u_{j,t}^{DG} - u_{j,t-1}^{DG} )$ $+ \sum_T^{t=1} \left( \sum_L^{i=1} P_{i,t}^{PHEV} B_{i,t}^{PHEV} + P_t^{Grid} B_t^{Grid} \right)$ <p>TSC is the total schedule cost; <math>L</math> is the total number of PHEV; <math>M</math> is the total number of DG units; <math>u_{j,t}^{DG}</math> is the status of the <math>j</math>th DG unit at hour <math>t</math>; <math>P_{j,t}^{DG}</math> (kW) is the active power production of the <math>j</math>th DG unit at hour <math>t</math>; <math>S_{j,t}^{DG}</math> (\$) is the start-up or shut-down cost of the <math>j</math>th DG unit; <math>B_{i,t}^{PHEV}</math> (\$) is the bid of the <math>j</math>th PHEV at hour <math>t</math>; <math>B_{j,t}^{DG}</math> (\$) is the bid of the <math>j</math>th DG unit at hour <math>t</math>; <math>B_t^{Grid}</math> (\$) is the energy bid of the utility at hour <math>t</math>.</p>	Metaheuristic (GA)	The proposed planning model provides the DNO (distribution network operator) a set of optimal solutions over a range of operating conditions and uncertainties.
[24]	$\min \sum_{\{l_k, \{z_k\}_k} p_B^T l_k + \frac{\rho}{2} \ l_k - z_k\ _2^2 + C_2 f_0 \left( \sum_k z_k \right)$ <p><math>z_k</math> is the auxiliary variable; <math>p_B</math> is the base price; <math>l_k</math> is the <math>k</math>th user load; <math>\rho</math> is the quadratic coefficient for augmented</p>	Classical (NLP)	Demand curve can be flattened after numerical examples of optimization

Reference	Objective function(s)	Optimization technique	Findings
[25]	<p>Lagrangian; <math>C_2</math> is the coefficient for fluctuation price; <math>f_0</math> is the variance of aggregated demand load.</p> $\min_{n,p} \sum_{t=1}^T \sum_{i=1}^N \left[ H_{i,t}(n) + \left( A_i n_{i,t} + \sum_{j=1}^J p_{i,j,t} B_{i,j} \right) \right]$ <p><math>i</math> is the generator group; <math>t</math> is the time intervals; <math>H_{i,t}</math> is the start-up cost of group <math>i</math> at time <math>t</math>; <math>A_i</math> is the no-load cost of one unit of group <math>i</math>; <math>B_{i,j}</math> is the marginal cost of segment <math>j</math> of the group <math>i</math>'s cost function; <math>n_{i,t}</math> is the integer of commitment decisions; <math>p_{i,j,t}</math> is the output for segment <math>j</math> of group <math>i</math> at time <math>t</math>.</p>	Classical (MILP)	Controlled charging can substantially reduce the cost of supplying additional EV demand due to lowered usage of peak generators, avoiding wind/solar curtailment, reduce carbon emission and associated costs, and reduce thermal generator start-up times.
[26]	$\min \{ Cost - Revenue \}$ $= \left\{ \left( \sum_{N=1}^{i=1} \sum_{T=1}^{h=1} Cost_{i,h}^{CHP} + \sum_{N=1}^{i=1} \sum_{T=1}^{h=1} Cost_{i,h}^b \right) + \sum_{N=1}^{i=1} \sum_{T=1}^{h=1} Cost_{i,h}^{PV} + \sum_{T=1}^{h=1} e p_h * grid_h^{buy} \right\} - \left( \sum_{T=1}^{h=1} SC * e p_h * grid_h^{sell} \right)$ <p><math>Cost_{i,h}^{CHP}</math> is the cost of electricity production by CHP systems; <math>Cost_{i,h}^b</math> is the cost of heat production by the boilers; <math>Cost_{i,h}^{PV}</math> is the total operation cost of PV generation systems; <math>grid_h^{buy}</math> and <math>grid_h^{sell}</math> are the purchased and sold electricity from/to the upstream network; <math>e p_h</math> is the electricity price at hour <math>h</math> in the upstream network; <math>SC</math> is the sell coefficient; <math>N</math> is the number of buses; <math>T</math> is the number of intervals (hour).</p>	Classical (NLP)	The introduction of PV (photovoltaic) generation systems coupled with PV storage systems in IMGs (industrial microgrid) could have positive effects on their scheduling solution and minimizing the overall cost.
[27, 28]	$\min_{I_i(t), N_{V2G(t)}} TC = W_c \times (Fuel + Start - Up) + W_e \times Emission$ $= \left\{ E \left( \sum_{s \in S} \sum_{i=1}^N \sum_{t=1}^H [W_c (FC_i(P_i(t))) + SC_i(1 - I_i(t-1))] I_i(t) \right) \right\} + W_e (\psi_i EC_i(P_i(t)) I_i(t))$	Metaheuristic (PSO)	PSO was utilized to generate a successful schedule considering the stochastic nature of renewable energies, load and GVs in a smart grid. Valid



Reference	Objective function(s)	Optimization technique	Findings
[29]	<p><math>I_l(t)</math>, <math>N_{V2G(t)}</math> are the decision variables for the on/off state of units and number of GVs connected to the grid at time <math>t</math>; <math>FC_i(P_i(t))</math> is the fuel cost of a thermal unit <math>i</math> with <math>P_i(t)</math> being the output power of unit <math>i</math> at time <math>t</math>; <math>SC_i(t)</math> is the start-up cost for restarting the de-committed thermal unit <math>i</math>; <math>\psi_i</math> is the emission penalty factor of unit <math>i</math>; <math>EC_i()</math> is the emission cost function for unit <math>i</math>; weight factors <math>W_c</math> and <math>W_e</math> are used to increase the flexibility of the system; <math>N</math> is the number of units; <math>H</math> is the scheduling hours; <math>S</math> is the set of scenarios; <math>E(.)</math> is the expectation.</p> $\min \left[ \sum_t \sum_i (p^b \cdot F_{c,i}(P_{i,t}) + SU_{i,t} + SD_{i,t}) + \sum_t \sum_k p^b \cdot (SU_{k,t} + SD_{k,t}) + \sum_t \sum_v p^b \cdot C_{v,t} \right] + \left[ \sum_t \sum_i (F_{c,i}^r(\Delta_{i,t}^{\max \times})) \right] + \sum_s p^s \cdot \left[ \sum_t \sum_i F_{c,i}(P_{i,t}^s) + \sum_t \sum_k (SU_{k,t}^s + SD_{k,t}^s) + \sum_t \sum_v C_{v,t}^s \right]$ <p><math>p^b</math>, <math>p^s</math> are the probabilities of the base case solution, and the probability of a scenario <math>s</math>; <math>F_{c,(.)}</math>, <math>F_{c,(.)}^r</math> are the production/availability cost function of a thermal unit; <math>C_{(.)}^{(.)}</math> is the operation cost of PEV fleet; <math>\Delta_{(.)}^{\max \times}</math> is the maximum permissible power adjustment of a unit; <math>P_{(.)}^{(.)}</math> is the generation of a unit; <math>s</math> denotes a scenario; <math>SD_{(.)}^{(.)}</math> is the shutdown cost a unit; <math>SU_{(.)}^{(.)}</math> is the startup cost of a unit; <math>b_{m,(.)}</math> is the slope of segment <math>m</math> in a linearized charge/discharge curve; <math>i</math> denotes a thermal unit; <math>t</math> is the hour index; <math>v</math> denotes a PEV fleet.</p>	Classical (MIP)	<p>scenarios are derived from prior statistics, heuristics, and anecdotal experiences of the authors.</p> <p>Numerical tests demonstrate the effectiveness of the proposed approach for analyzing the impact of PEVs on the grid operation cost and hourly wind energy dispatch.</p>

**Table 1.** Optimization of V2G services for minimizing operational cost.

Reference	Objective function	Optimization technique	Findings
[30]	$\min_{u_1, u_2} \sum_T^{t=1} \{C_{\text{energy}}(u_1) + C_{\text{reserve},s}(R_s) + C_{\text{reserve},d}(R_d)\}$ <p><math>u_1</math> is the electricity generation; <math>u_2</math> is the scheduling of wind power; <math>C_{\text{energy}}</math> is the cost of electricity generation; <math>C_{\text{reserve},s}</math> is the reserve scheduling; <math>C_{\text{reserve},d}</math> is the expected reserve dispatch; <math>R_s</math> is the scheduling of conventional reserve (MW); <math>R_d</math> is the expected dispatch of conventional reserve (MW).</p>	Classical (DP)	Demonstrated the value of fully exploring the synergy between PEV and wind power using a three-level controller; with the top-level minimizing generation costs, mid-level allotting charging time and power based on battery SOC, and bottom-level using real-time feedback to attempt grid frequency synchronization.
[31]	$\min_{P_{G_i}^{(t)}, P_{L_j}^{(t)}, E_{VB_j}^{(0)}, \Delta E} \sum_{t=i}^T \sum_i n_{G_i} \cdot P_{G_i}^{(t)}$ <p><math>P_{G_i}</math> is the power produced by generator <math>G_i</math>; <math>n_{G_i}</math> is the marginal cost of generator <math>G_i</math>; <math>P_{L_j}</math> is the power consumed by load <math>L_j</math>; <math>E_{VB_j}</math> is the energy content of the virtual battery; <math>\Delta E</math> is the shift in the energy content of the aggregation of virtual batteries.</p>	Hybrid (Classical and scenario method)	Compared to a pure cost-optimizing strategy, part of the charging has to be moved from the night to more expensive hours to reduce the SOC swing. This leaves enough flexibility to compensate the forecast error.
[32]	$\min E   C_{\text{total}}  $ $C_{\text{total}} = \sum_{i=1}^{N_c} C_i(P_{s,i}) + \sum_{i=1}^{N_w} C_{w,i}(W_{s,i}) + \sum_{i=1}^{N_w} C_{w,u,i}(W_{s,i}, W_i) + \sum_{i=1}^{N_w} C_{w,o,i}(W_{s,i}, W_i) + \sum_{i=1}^{N_e} C_{e,i}(P_{e,s,i}) + \sum_{i=1}^{N_e} C_{e,u,i}(P_{e,i}, P_{e,s,i}) + \sum_{i=1}^{N_e} C_{e,o,i}(P_{e,i}, P_{e,s,i})$	Hybrid (Interior point based PSO)	By studying the statistical properties of charging and discharging EVs along with formulating a power system economic dispatch model, which takes into account impacts of EVs and wind

Reference	Objective function	Optimization technique	Findings
	<p><math>N_c</math> is the number of conventional generators; <math>N_w</math> is the number of wind generators; <math>N_e</math> is the number of buses with V2G facilities installed; <math>C_i</math> is the conventional generator cost; <math>P_{s,i}</math> is the scheduled output of the conventional generator <math>i</math>; <math>C_{w,i}</math> is the wind generator cost; <math>W_i</math> is the available wind power; <math>W_{s,i}</math> is the scheduled output of the wind generator <math>i</math>; <math>C_{w,u,i}</math> is the underestimating penalty cost coefficient; <math>C_{w,o,i}</math> is the overestimating penalty cost coefficient; <math>P_{\sigma,i}</math> is the available V2G power at bus <math>i</math>; <math>P_{e,s,i}</math> is the scheduled V2G power at bus <math>i</math>.</p>		generators, a novel algorithm is proposed to solve nonlinear and nonconvex optimization problems.
[33]	$\min_{u_1, u_2} \sum_t \{C_{conv} \cdot (u_1 + r') + CA.S.(r)\}$ <p><math>C_{conv}</math> is the cost of conventional generators; <math>CA.S.</math> is the cost of ancillary services; <math>u_1, u_2</math> are the control variables representing the scheduling of conventional generators and ancillary services; <math>r</math> is the scheduling of ancillary services; <math>r'</math> is the expected dispatch of ancillary services.</p>	Classical (DP)	The proposed integration is an implementable algorithm to realize the synergy of PEV charging and wind energy. It can also be made to reflect other inherently stochastic RESs.
[34]	$\min \left( \sum_{i \in NG} \alpha_i \Delta P_{gi} + \sum_{i \in ND} \beta_i \Delta P_{di} \right)$ <p><math>i^{th}</math> is the index bus bar; <math>\alpha_i</math> is the coefficient of generation curtailment; <math>\beta_i</math> is the coefficient of load shedding; <math>\Delta P_{di}</math> is the load shedding; <math>\Delta P_{gi}</math> is generation curtailment; <math>NG, ND</math> are the sets of generation and load demand.</p>		It is found that active network management (ANM) strategies achieved through intelligent EV charging can further reduce generation curtailment; allowing for more absorption of renewable energy.

**Table 2.** Optimization of V2G services for minimizing generation cost.

#### 4.2.1.2. Generation cost optimization

Generation cost optimization is crucial to both power distributors, charging station operators, and the EV owners. Interactions between EVs and RESs through the smart grid are at the center of intensive research. Maximizing the profit for distributors, minimizing cost of operation/generation, and the cost of ownership and charging of EV is crucial with the proliferation of

green energy [3]. **Table 2** summarizes the related research works, their objective functions, techniques in use for optimization, and their main findings.

#### 4.2.1.3. Profit/benefit optimization

By maximizing the profit for generators/providers, or the benefits for providing energy, the effects are felt by the supply chain through aggregators, charging stations, etc. down to the EV owners. Optimization is referenced from the viewpoint of increasing investments in RESs or electricity delivery management. **Table 3** summarizes the related research works, their objective functions, techniques in use for optimization, and their main findings.

#### 4.2.1.4. Charging cost optimization

Minimizing costs is crucial to both distributors and EV owners. Ensuring that the costs stay low on the distribution side ensures that costs stay low on the consumer side. Maximizing the synergy between stochastic RES generation and EV charging loads is the key to minimizing the costs surrounding EVs [3]. **Table 4** summarizes the related research works, their objective functions, techniques in use for optimization, and their main findings.

Reference	Objective function	Optimization technique	Findings
[35]	$\max_{x,b,d,y,g} P(x, d) = \sum_{n=0}^{N-1} p^e(n)[x(n) + d(n)]$ <p><math>x</math> is the energy supplied directly to the grid; <math>b</math> is the energy transferred to the batteries; <math>d</math> is the energy transferred from the batteries; <math>y</math> is the needed storage capacity; <math>g</math> is the energy transferred to the batteries as payment; <math>P()</math> is the revenues raised by the virtual power plant (VPP) from the electricity sold at market; <math>p^e(n)</math> is the wholesale price of electricity.</p>	Classical (Iterative LP)	VPP formed with EVs can maximize profits by optimizing the schedule of supply to the grid based on the wind energy production and the available storage.
[36]	$\min_u - \left\{ \sum_h p^h \sum_i x_i^h - \sum_h c^h \cdot y^h - E_{\xi} \sum_h \{ r^h(\xi) \cdot z^{h*}(\xi) - q^h \cdot v^{h*}(\xi) \} \right\}$ <p><math>x_i^h</math> is the allocation of energy to EV <math>i</math> for hour <math>h</math>; <math>y^h</math> is the amount of purchased bulk energy for hour <math>h</math>; <math>p^h</math> is the price per energy unit at which energy is charged to the EVs during hour <math>h</math> by the aggregator; <math>c^h</math> is the price of bulk</p>	Classical (SP)	A stochastic-based framework is proposed for smart grid operators to determine optimal charging control of EVs and energy purchasing to

Reference	Objective function	Optimization technique	Findings
[37]	<p>energy for hour <math>h</math>; <math>r^h(\xi)</math> is the price of energy in the real-time market; <math>q^h</math> is the price at which excess energy is purchased back; <math>z^h</math> is the real-time energy purchased back by the aggregator; <math>v^h</math> is the excess energy sold back.</p> $\min_{I \in \mathcal{I}} \frac{S_{\text{online}}(I)}{S_{\text{offline}}^*(I)} \geq \alpha$ <p><math>\mathcal{I}</math> is the input set fixed for all input instances <math>I</math> with finite sizes; <math>S_{\text{online}}(I)</math> is the total profit obtained by the online scheduler; <math>S_{\text{offline}}^*(I)</math> is the optimal offline scheduler.</p>	Classical (Threshold admission and greedy scheduling (TAGS))	maximize performance.  It is shown that, when the price offered to the EV customers is higher than the purchasing price of electricity from the grid, TAGS achieves the competitive ratio of 1.
[38]	$\max_{POP_i(t), MxAP_i(t), MInAP_i(t)} In - C$ $In = \alpha \sum_t (P_{\text{regUp}}(t)R_{\text{Up}}(t) + P_{\text{regDown}}(t)R_{\text{Down}}(t)) + Mk \sum_i \sum_t (E(PD_i(t)))$ <p><math>In - C</math> is the aggregator income minus costs; <math>Mk</math> is the aggregator markup over wholesale energy price; <math>\alpha</math> is the percentage of regulation revenue taken by the aggregator; <math>R_{\text{Up}}</math> is the bid regulation up capacity of the aggregator; <math>R_{\text{Down}}</math> is the bid regulation down capacity of the aggregator; <math>PD_i</math> is the power draw of the battery of the <math>i</math>th EV.</p>	Classical (CP)	Simulations of hourly, daily, and yearly show that the optimal algorithms increase aggregator profits, lower load demand, and reduce costs to customers.
[17]	$\max \text{V2G Income} = \sum_{t=1}^T \left[ \left( \sum_{V=1}^{N_V} (P_{\text{Discharge}(V,t)} \times C_{\text{Discharge}(V,t)} - P_{\text{Charge}(V,t)} \times C_{\text{Charge}(V,t)}) \right) \times \Delta t \right]$ <p><math>N_V</math> is the total number of vehicles <math>V</math>; <math>P_{\text{Discharge}(V,t)}</math> is the power discharge of vehicle <math>V</math> in period <math>t</math>; <math>c_{\text{Discharge}(V,t)}</math> is the discharge price of vehicle <math>V</math> in period <math>t</math>; <math>P_{\text{Charge}(V,t)}</math> is the power charge of vehicle <math>V</math> in period <math>t</math>; <math>c_{\text{Discharge}(V,t)}</math> is the charge price of vehicle <math>V</math> in period <math>t</math>.</p>	Metaheuristic (parallel PSO)	The parallelization approach presented provides promising results to model EV loads on distribution networks for future incorporation of smart grid technologies

**Table 3.** Optimization of V2G services for maximizing profits/benefits.



Reference	Objective function	Optimization technique	Findings
[39]	$\min_{u_{i,t}} \sum_{t=1}^{N_t} (C_t^N + \alpha_t) Q_{EV,t} + \beta Q_{EV,t}^2$ <p><math>u_{i,t}</math> is the optimization variable representing the charging rate of vehicle <math>i</math> out of a total number of vehicles at time <math>t</math>; <math>C_t^N</math> is the time-dependent network tariff; <math>\alpha_t</math> is the baseline electricity price at time <math>t</math>; <math>Q_{EV,t}</math> is the extra demand of the EVs; <math>\beta Q_{EV,t}^2</math> is the EV-dependent part.</p>	Classical (Rolling horizon optimization scheme)	An analysis of EV-caused distribution network congestion management is presented and a mathematical model of optimization is proposed.
[40]	$\min_{x_g(t)} V \gamma(t) y(t) - \sum_{g=1}^G \left[ Q_g(t) \left( 1 + \frac{\eta}{R_g} \right) + Z_g(t) \right] x_g(t)$ <p><math>x_g(t)</math> is the control variable; <math>V</math> is a parameter that is used to tune the tradeoff between cost and queue backlog growth; <math>\gamma(t)</math> is the electricity price at time <math>t</math>; <math>y(t)</math> is an auxiliary variable; <math>Q_g(t)</math> the total charging tasks in timeslot <math>t</math> of <math>g</math> queues; <math>Z_g(t)</math> is the virtual queue; <math>R_g</math> is the max charging time; <math>\eta</math> is a constant to adjust the growth rate of the virtual queue.</p>	Classical (Lyapunov optimization)	A stochastic optimization problem is formulated to describe the queuing problem for EV charging requests and minimize the time average cost of using other energy sources when renewable sources are unable to meet demand.
[41]	$\min (EC) = \min \left( \sum_{t=t_a}^{t_b} P_t \times SP_t \right)$ <p><math>EC</math> is the energy costs of the PEV; <math>P_t</math> is the charge/discharge power at hour <math>t</math>; <math>SP_t</math> is the spot hour price at hour <math>t</math>; <math>t_a</math> is the starting hour of charge/discharge for the PEV; <math>t_b</math> is the ending hour of charge/discharge for the PEV.</p>	Classical (Sequential quadratic programming)	The optimization method presented has shown that PEV charging/discharging during optimal spot market times minimize energy costs on low wind-generated power days.
[42]	$\min \sum_{t=1}^T \alpha q_t + \beta q_t^2$ <p><math>q_t</math> are the total purchases and sales of the aggregator; <math>\alpha, \beta</math> are variables linearly relating price to load.</p>	Classical (Quadratic programming)	This paper offers to aggregators a framework of optimizing charging and discharging of EV fleets given driving patterns and spot market prices.

**Table 4.** Optimization of V2G services for minimizing EVs' charging cost.

#### 4.2.1.5. Other cost-related optimization

Other cost-related optimizations include minimizing overall costs related to system lifetime, transmission, materials and resources, upgrades, losses, and renewable imbalances [3]. **Table 5** summarizes the related research works, their objective functions, techniques in use for optimization, and their main findings.

#### 4.2.2. Efficiency optimization

The efficient utilization of renewables can reduce the use of fossil energy quite substantially. This can elicit several benefits including air pollution reduction and cost savings for consumers. The efficiency-related optimization objectives in regards to EVs interactions with RESs are maximizing RES utilization, optimizing energy dispatch, optimizing energy management, minimizing power loss, and minimizing energy loss. Sections 4.2.2.1 and 4.2.2.2 provide details regarding the efficiency-related optimization works for EVs interacting with RESs.

Reference	Objective function	Optimization technique	Findings
[43]	$\min_{\Omega} ([f_1(\Omega)f_2(\Omega)])$ $f_1(\Omega) = NPV_{\text{upgrades}} + NPV_{\text{losses}}$ $f_2(\Omega) = E_{\text{grid}} + E_{\text{DG}} - E_{\text{PEV}}$ <p><math>NPV_{\text{upgrades}}</math> is the net present value (NPV) of the costs of upgrades; <math>NPV_{\text{losses}}</math> is the NPV of the costs of losses; <math>E_{\text{grid}}</math> are the emissions due to energy purchased from the grid; <math>E_{\text{DG}}</math> are the emissions of distributed generation (DG) units; <math>E_{\text{PEV}}</math> are the emission reductions of the PEV.</p>	Metaheuristic (Nondominated sorting genetic algorithm (NDSGA))	A planning method is presented that can accommodate a high penetration of PEV and renewable DG into preexisting distribution networks.
[44]	$\min C = C_{\text{DG}} + C_{\text{S}} + C_{\text{G}} + C_{\text{M}}$ <p><math>C</math> is the lifecycle cost of the system; <math>C_{\text{DG}}</math> and <math>C_{\text{S}}</math> are the initial capital costs for the renewable DG and the storage unit; <math>C_{\text{G}}</math> is the cost associate with getting energy from the grid; <math>C_{\text{M}}</math> is the maintenance cost of the system.</p>	Classical (MILP)	A methodology is presented to design grid-interfaced PEV charging stations that integrate RE generation and distribution networks
[45]	$\min \sum_{t=1}^{24} aP_{\text{Conv}}^2(t) + bP_{\text{Conv}}(t) + c$	Metaheuristic (GA)	This paper generates a smart energy management system

Reference	Objective function	Optimization technique	Findings
	$a, b, c$ are cost coefficients; $P_{Conv}(t)$ is the generation of the conventional generator at time $t$ .		(EMS) that allows distributors a more economical means of incorporating wind resources and EV storage solutions into existing generation resources.
[46]	$\min \{C_{Pen.} + C_{V2G} - R_{V2G}\}$ <p><math>C_{Pen.}</math> is the penalty cost for wind power imbalances;  <math>C_{V2G}</math> is the cost for V2G services; <math>R_{V2G}</math> is the revenue for V2G services.</p>	Hybrid (GA-based Monte Carlo simulation (MCS))	The proposed optimization provides collaboration between wind participants and EV aggregators to minimize the sum of the penalty cost associated with wind power imbalances and V2G expenses associated with purchased energy, battery degradation and capital costs as well as increasing the EVs' revenues and incentives.
[47]	$\min \sum_{k=1}^K C_{Pen.}(t_k)$ <p><math>C_{pen}</math> is the penalty cost for PV power imbalances;  <math>K</math> is the number of time steps.</p>	Hybrid (PSO-based Monte Carlo simulation (MCS))	This paper proposes a coordinated charging/discharging scheme to optimally utilize V2G capacities of EVs to minimize the penalty cost for PV power under-/overproduction.

**Table 5.** Optimization of V2G services for minimizing costs.

#### 4.2.2.1. RES utilization maximization

The excessive power generated by RESs can be stored in batteries of the EV fleets and DC-link capacitors in specialized charging stations to supply the necessary power through V2G infrastructure when the renewable energy generation is insufficient to meet load demands. An optimization strategy is required to coordinate the EVs' charging/discharging with RESs uncertainties to maximize the use of renewable generation. **Table 6** summarizes the related research works, their objective functions, techniques in use for optimization, and their main findings.

Reference	Objective function	Optimization technique	Findings
[48]	$\max_{\varphi_t} \rightarrow \overline{\text{RES}} = \sum_{t=1}^T \text{res}_t \cdot \varphi$ <p><math>\text{res}_t</math> is the share of RES of total load in time step <math>t</math> (%); <math>\varphi_t</math> is the charge parameter for time step <math>t</math>.</p>	Classical (LP)	Through the optimization objective of maximizing amount of charging power coming from RES through the smart grid during optimal times, the authors were able to see that RES made up 83% of the EVs' charging demand.
[49]	$\min_{\varphi, \text{ramp}_t, \text{isOn}_t} f = \sum_{t \in 1..T} \text{CG}_t$ <p><math>\text{CG}_t</math> is the conventional generation in time slot <math>[t - 1, t]</math>;  <math>\text{ramp}_t</math> is the occurrence of ramping for time slot <math>[t - 1, t]</math>; <math>\varphi</math> is the maximum charge amount in one time slot;  <math>\text{isOn}_t</math> is the binary state variable for conventional generation.</p>	Classical (MIP)	The findings presented suggest that through an optimal charging algorithm controlling the scheduling of EV fleet charging, the usage of renewables can double; with wind alone supplying 67.2%.

Reference	Objective function	Optimization technique	Findings
[50]	$C_{\text{tot}}(t) = \min \left( \sum_{n=1}^{NTU} (C_{\text{start},n} + (PC_n(P_{TU_n})^{NTU} + C_{\text{ems},n}(P_{TU_n}) \cdot t_{\text{int}}) \right)$ <p>is the number of thermal units;  <math>C_{\text{tot}}(t)</math> is the total production cost; <math>C_{\text{start},n}</math> is the startup cost of unit <math>n</math>;  <math>PC_n</math> is the production cost of unit <math>n</math>; <math>C_{\text{ems},n}</math> is the CO<sub>2</sub> emission cost of unit <math>n</math>; <math>P_{TU_n}</math> is the output power of unit <math>n</math>; <math>t_{\text{int}}</math> is the time period share in an hour.</p>	Classical (MIP)	<p>This paper suggests a strategy to fully supply the EVs' charging load by RESs within a microgrid composing of a photovoltaic plant, a thermal unit, battery energy storage systems, and electric vehicle charging stations.</p>
[51]	$J_{\tilde{u}^*}(x_0) = \max_{\tilde{u} \in U} J_{\tilde{u}}(x_0)$ $J_{\tilde{u}}(x_0) = \lim_{T \rightarrow \infty} \frac{1}{T} E \left\{ \int_0^T r(x(t), a(t)) dt \right\}$ <p><math>\tilde{u}^*</math> is the optimal charging policy; <math>r(x(t), a(t))</math> is the reward for the action <math>a(t)</math> taken in a state <math>x(t)</math>.</p>	Classical (LP)	<p>The authors developed an optimal charging policy strategy to maximize renewable energy utilization within preexisting distribution infrastructure despite stochastic generation potential.</p>
[52]	$\min_{x_t^k} \left\{ \sum_{t=1}^T C_t \left( \sum_{k=1}^K x_t^k \right) + \sum_{k=1}^K \sum_{t=1}^T D_t^k(x_t^k) \right\}$ <p><math>C_t(\cdot)</math> is the imbalance cost; <math>D_t^k(\cdot)</math> is the disutility of the subscribers that aid in balancing; <math>x_t^k</math> is the energy demand of subscriber <math>k</math> during time slot <math>t</math>.</p>	Classical (Convex optimization-quadratic) programming	<p>The authors proposed an optimal distributed algorithm to balance the synergy of smartgrid interactions between RES supply and EV charging demand.</p>



Reference	Objective function	Optimization technique	Findings
[53]	$\text{Min } \left\{ J = \sum_{h=1}^H \sum_{p=1}^{h-1} \left( (x_{h,p} - b_{h,p}) \cdot (K_p \rho_p - \sum_{r=1}^{NG} K_r P_{r,p}) \right) \right\}$ <p><math>J</math> is the objective function; <math>x_{h,p}</math> is the purchased and charged energy at hour <math>p</math>; <math>b_{h,p}</math> is the available energy in the batteries of EDVs that is used in hour <math>h</math>; <math>H</math> is the number of hours in the assessed time period;</p> <p><math>P_{r,p}</math> is the production of RES <math>r</math> in hour <math>p</math> among NG RESs; <math>\rho_p</math> is the purchase energy price in the market in hour <math>p</math>; <math>K_p</math> and <math>K_r</math> are the optimization parameters that regulate the objective function <math>J</math>.</p>	Classical (LP)	Higher transportation costs for EDV users present a tradeoff for a cleaner environment through reduced emissions as a result of more intensive RES exploitation in transportation.

**Table 6.** Optimization of V2G services for maximizing RES utilization.

#### 4.2.2.2. Other efficiency-related optimization

Other efficiency-related optimizations include minimizing imported electricity [54], minimizing power loss [55], minimizing loss energy, and optimizing energy management [56], etc. Table 7 below summarizes the related research works, their objective functions, techniques in use for optimization, and their main findings.

Reference	Objective function	Optimization technique	Findings
[54]	$\min \left( \theta^T - \rho(h) \cdot \sum_{h=1}^H E(h) \right)$ <p><math>\rho(h)</math> is the unit price of the electricity consumption; <math>E(h)</math> is the electricity in (kwh) generated from renewable energy sources in time slot (hour) <math>h</math>; <math>\theta^T</math> is the total daily electricity cost.</p>	Classical (MILP)	The results of the simulations conducted in this paper show that intelligent, optimized scheduling of EV fleets drastically increases

Reference	Objective function	Optimization technique	Findings
[55]	$F = \min[(f_1 + f_2) + \sum_{i \in N_{DG}} (\max(V_i - V_i^{\max}, 0)) + \max(V_i^{\min} - V_i, 0) + \sum_{i \in N} \max( S_i  -  S_i^{\max} , 0)]$ <p><math>f_1</math> is the power losses of <math>N</math>-bus distribution system; <math>f_2</math> is the error between rated voltage (1 p.u) and voltage of each bus;  <math>V</math> is the voltage; <math>N_{DG}</math> is the total number of system suppliers.</p>	Metaheuristic (GA)	overall distribution performance, reducing charging times and related costs. The focus of this paper is on improving the "smart parking lot," with a primary goal of efficiently reducing power losses through improving voltage profiles and optimized scheduling of EV fleet charging during peak and nonpeak hours.
[56]	$\text{Min } C = \sum_{S c_{\text{wind}}}^H \pi(S c_{\text{wind}}) \sum_{t=0}^{N-1} \left[ \sum_{i=1}^I C_{DGU_{i,t}} \cdot (P_{DGU_{i,t}, S c_{\text{wind}}}) + C_{\text{grid},t} \cdot (P_{\text{grid},t}) + \sum_{j=1}^J C_{GAR_{j,t}} \cdot (P_{GAR_{j,t}, S c_{\text{wind}}}) \right]$ <p><math>\pi(S c_{\text{wind}})</math> is the probability/weight of wind scenario <math>S c_{\text{wind}}</math>; <math>S c_{\text{wind}}</math> is the index of wind power scenarios running from 1 to <math>H</math>; <math>C_{DGU_{i,t}}</math> is the price of energy obtained from dispatch-able generating unit <math>i</math> at time <math>t</math>; <math>P_{DGU_{i,t}, S c_{\text{wind}}}</math> is the power output from dispatch-able generating unit <math>i</math> at time <math>t</math> and under wind power scenario <math>S c_{\text{wind}}</math>; <math>C_{\text{grid},t}</math> is the price of energy obtained from the main grid at time <math>t</math>; <math>P_{\text{grid},t}</math> is the power input/output for the main grid at time <math>t</math>; <math>C_{GAR_{j,t}}</math> is the price of energy obtained from garage <math>j</math> at time <math>t</math>; <math>P_{GAR_{j,t}, S c_{\text{wind}}}</math> is the power input/output for garage <math>j</math> at time <math>t</math> and under wind power scenario <math>S c_{\text{wind}}</math></p>	Classical (LP)	The practical model provided in this paper assesses the ability of V2G systems to provide power support to conventional grid operations, including small electric energy systems (SEES).

**Table 7.** Optimization of V2G services for improving efficiency.

### 4.2.3. Emission optimization

Emission reduction is one of the most important objectives of EVs' adoption for transportation. This objective can be further satisfied through interactions between EVs and RESs. V2G implementation plays a key role in this scenario to decrease the power utility costs and protect the environment. Related research works include references [27] and [28] of **Table 1**, reference [43] of **Table 5**, and reference [57] whose objective function, optimization technique, and its main finding is provided in **Table 8**.

Reference	Objective function	Optimization technique	Findings
[57]	$\text{Minimize } J = \sum_0^{24} \left( \frac{\text{CO}_2}{\text{gal}} * m_f * \Delta t_{dr} + \frac{\text{CO}_2}{\text{kWh}} * P_b * \Delta t_{ch} \right)$ <p><math>J</math> is the optimization objective; <math>m_f</math> is the gasoline consumption; <math>P_b</math> is the battery charging power; <math>\Delta t_{ch}</math> is the charging time step  <math>\Delta t_{dr}</math> is the driving time step.</p>	Classical (DP)	The proposed integrated approach shows, through successful simulations, that with more wind-based power generation and integration into existing distribution infrastructure comes a reduction in carbon dioxide emissions.

**Table 8.** Optimization of V2G services for reducing emission.

### Author details

Mahmoud Ghofrani<sup>1\*</sup>, Eric Detert<sup>1</sup>, Negar Niromand Hosseini<sup>1</sup>, Amirsaman Arabali<sup>2</sup>, Nicholas Myers<sup>1</sup> and Phasith Ngin<sup>1</sup>

\*Address all correspondence to: [mrani@uw.edu](mailto:mrani@uw.edu)

<sup>1</sup> Electrical Engineering, Engineering and Mathematics Division, School of STEM, University of Washington Bothell, Bothell, Washington, USA

<sup>2</sup> LCG Consulting, Los Altos, California, USA

## References

- [1] Mwasilu F., Justo J.J., Kim E., Do T.D., Jung J.W. Electrical vehicle and smart grid interaction: A review on vehicle to grid and renewable energy source integration. *Renewable and Sustainable Energy*. 2014; 34:501–516.
- [2] Yong J.Y., Ramachandaramurthy V.K., Tan K.M., Mithulananthan N. A review on the state-of-the-art technologies of the electrical vehicle, its impacts and prospects. *Renewable and Sustainable Energy Reviews*. 2015; 49:365–385.
- [3] Liu L., Kong F., Lui X., Peng Y., Qinglong W. A review on electric vehicles interacting with renewable energy in smart grid. *Renewable and Sustainable Energy Reviews*. 2015; 51:648–661.
- [4] Wikipedia. Nissan Leaf [Internet]. [Updated: 4/15/2016]. Available from: [https://en.wikipedia.org/wiki/Nissan\\_Leaf](https://en.wikipedia.org/wiki/Nissan_Leaf) [Accessed: 4/17/2016]
- [5] Wikipedia. Toyota Prius [Internet]. [Updated: 4/14/2016]. Available from: [https://en.wikipedia.org/wiki/Toyota\\_Prius](https://en.wikipedia.org/wiki/Toyota_Prius) [Accessed: 4/17/2016]
- [6] Tan K.M., Ramachandaramurth V.K., Yong J.Y. Integration of electrical vehicle in smart grid: A review on vehicle to grid technologies and optimization techniques. *Renewable and Sustainable Energy Reviews*. 2016; 53:720–732.
- [7] Kempton W., Letendre S. Electric vehicles as a new power source for electric utilities. *Transportation Research Part D- Transportation and Environment*. 1997; 2(3):157–175.
- [8] Canada NewsWire. Global Smart Grid Federation Publishes Report on Learning Smart Grid Project Around the World. 2012.
- [9] Amoroso F., Cappuccino G. Advantages of efficiency-aware smart charging strategies for PEVs. *Energy Conversation & Management*. 2012; 54(1):1–6.
- [10] Li H., Lai L., Qiu R.C. Scheduling of wireless metering for power market pricing in smart grid. *IEEE Transactions on Smart Grid*. 2012; 3(4):1611–1620.
- [11] Kim T., Chang A.C.C., Li M., Rong C., Patrikakis C.Z., Sleza D. Communication and networking. In: *International Conference, FGCN 2010, Held as Part of the Future Generation Information Technology Conference, FGIT 2010; December 13–15, 2010; Jeju Island, Korea*. Berlin: Springer; 2010. pp. 199–206.
- [12] Monterio V., Pinto J.G., Exposto B., Goncalves H., Ferreira J.C., Couto C., et al. Assessment of a battery charger for electric vehicles with reactive power control. In: *Proceedings of the IEEE IECON 2012: 38th Annual Conference on Industrial Electronics Society; October 25–28, 2012*. pp. 5142–5147.
- [13] Han S., Han S., Sezaki K. Development of an optimal vehicle-to-grid aggregator for frequency regulation. *IEEE Transactions on Smart Grid*. 2010; 1(1):65–72.

- [14] Mullan J., Harries D., Bräunl T., Whitely S. The technical economic and commercial viability of the vehicle-to-grid concept. *Energy Policy*. 2012; 48:394–406.
- [15] Sortomme E., El-Sharkawi M.A. Optimal scheduling of vehicle-to-grid energy and ancillary services. *IEEE Transactions on Smart Grid*. 2012; 3(1):351–359.
- [16] Ghanbarzadeh T., Goleijani S., Moghaddam M.P. Reliability constrained unit commitment with electric vehicle to grid using hybrid particle swarm optimization and ant colony optimization. In: *Proceedings of the IEEE power and energy society general meeting*; July 24–29, 2011. pp. 1–7.
- [17] Soares J., Vale Z., Canizes B., Morais H. Multi-objective parallel particle swarm optimization for day-ahead vehicle-to-grid scheduling. In: *Proceedings of the IEEE CIASG 2013: Symposium on Computational Intelligence Applications in Smart Grid*; April 16–19, 2013. pp. 138–145.
- [18] Díaz-González F., Sumper A., Gomis-Bellmunt O., Villafáfila R. A review of energy storage technologies for wind power applications. *Renewable and Sustainable Energy Reviews*. 2012; 16(4):2154–2171.
- [19] Leemput N., Geth F., Claessens B., Van Roy J., Ponnette R., Driesen J. A case study of coordinated electric vehicle charging for peak shaving on a low voltage grid. *IEEE Innovative Smart Grid Technologies (ISGT Europe)*; 2012.
- [20] Kesler M., Kisacikoglu M.C., Tolbert L.M. Vehicle-to-grid reactive power operation using plug-in electric vehicle bidirectional off-board charger. *IEEE Transactions on Industrial Electronics*. 2014; 61(12):6778–6784.
- [21] Yong J.Y., Ramachandaramurthy V.K., Tan K.M., Mithulananthan N. Bi-directional electric vehicle fast charging station with novel reactive power compensation for voltage regulation. *International Journal of Electrical Power & Energy Systems*. 2015; 64:300–310.
- [22] Zhang M., Chen J. The energy management and optimized operation of electric vehicles based on microgrid. *IEEE Transactions on Power Delivery*. 2014; 29:1427–1435.
- [23] Chen C., Duan S. Optimal integration of plug-in hybrid electric vehicles in microgrids. *IEEE Transactions on Industrial Informatics*. 2014; 10:1917–1926.
- [24] Tan Z., Yang P., Nehorai A. An optimal and distributed demand response strategy with electric vehicles in the smart grid. *IEEE Transactions on Smart Grid*. 2014; 5:861–869.
- [25] Aunedi M., Strbac G. Efficient system integration of wind generation through smart charging of electric vehicles. In: *Proceedings of 8th International Conference and Exhibition on Ecological Vehicles and Renewable Energies (EVER)*; 2013. pp. 1–12.
- [26] Derakhshandeh S., Masoum A.S., Deilami S., Masoum M.A., Hamedani Golshan M. Coordination of generation scheduling with PEVs charging in industrial microgrids. *IEEE Transactions on Power Systems*. 2013; 28:3451–3461.

- [27] Saber A.Y., Venayagamoorthy G.K. Resource scheduling under uncertainty in a smart grid with renewables and plug-in vehicles. *IEEE Systems Journal*. 2012; 6:103–109.
- [28] Saber A.Y., Venayagamoorthy G.K. Plug-in vehicles and renewable energy sources for cost and emission reductions. *IEEE Transactions on Industrial Electronics*. 2011; 58:1229–1238.
- [29] Khodayar M.E., Wu L., Shahidehpour M. Hourly coordination of electric vehicle operation and volatile wind power generation in SCUC. *IEEE Transactions on Smart Grid*. 2012; 3:1271–1279.
- [30] Li C.T., Ahn C., Peng H., Sun J. Synergistic control of plug-in vehicle charging and wind power scheduling. *IEEE Transactions on Power Systems*. 2013; 28:1113–1121.
- [31] Vayá M.G., Andersson G. Integrating renewable energy forecast uncertainty in smart-charging approaches for plug-in electric vehicles. In: *IEEE Grenoble PowerTech (POWERTECH)*; 2013. pp. 1–6.
- [32] Zhao J., Wen F., Dong Z.Y., Xue Y., Wong K.P. Optimal dispatch of electric vehicles and wind power using enhanced particle swarm optimization. *IEEE Transactions on Industrial Informatics*. 2012; 8:889–899.
- [33] Li C.T., Ahn C., Peng H., Sun J. Integration of plug-in electric vehicle charging and wind energy scheduling on electricity grid. In: *IEEE Innovative Smart Grid Technologies (ISGT)*; 2011. pp. 1–7.
- [34] Zhou L., Li F., Gu C., Hu Z., le Blond S. Cost/benefit assessment of a smart distribution system with intelligent electric vehicle charging. *IEEE Trans. Smart Grid*. 2014; 5:839–847.
- [35] Vasirani M., Kota R., Cavalcante R.L., Ossowski S., Jennings N.R. An agent-based approach to virtual power plants of wind power generators and electric vehicles. *IEEE Transactions on Smart Grid*. 2013; 4:1314–1322.
- [36] Goonewardena M., Le L.B. Charging of electric vehicles utilizing random wind: A stochastic optimization approach. In: *IEEE Globecom Workshops (GC Wkshps)*; 2012. pp. 1520–1525.
- [37] Chen S., Tong L. IEMS for large scale charging of electric vehicles: architecture and optimal online scheduling. In: *Proceedings of IEEE 3rd International Conference on Smart Grid Communications (SmartGridComm)*; 2012. pp. 629–634.
- [38] Sortomme E., El-Sharkawi M.A. Optimal charging strategies for unidirectional vehicle-to-grid. *IEEE Transactions on Smart Grid*. 2011; 2(1):131–138.
- [39] Verzijlbergh R.A., de Vries L.J., Lukszo Z. Renewable energy sources and responsive demand. Do we need congestion management in the distribution grid? *IEEE Transactions on Power Systems*. 2014; 29 (5):2119–2128.



- [40] Jin C., Sheng X., Ghosh P. Energy efficient algorithms for electric vehicle charging with intermittent renewable energy sources. In: IEEE Power and Energy Society General Meeting (PES); 2013. pp. 1–5.
- [41] Hu W., Su C., Chen Z., Bak-Jensen B. Optimal operation of plug-in electric vehicles in power systems with high wind power penetrations. IEEE Transactions on Sustainable Energy. 2013; 4:577–585.
- [42] Kristoffersen T.K., Capion K., Meibom P. Optimal charging of electric drive vehicles in a market environment. Applied Energy. 2011; 88:1940–1948.
- [43] Shaaban M.F., El-Saadany E. Accommodating high penetrations of PEVs and renewable DG considering uncertainties in distribution systems. IEEE Transactions on Power Systems. 2014; 29:259–270.
- [44] Gunter S.J., Afridi K.K., Perreault D.J. Optimal design of grid-connected PEV charging systems with integrated distributed resources. IEEE Transactions on Smart Grid. 2013; 4:956–967.
- [45] Ghofrani M., Arabali A., Etezadi-Amoli M. Electric drive vehicle to grid synergies with large scale wind resources. In: IEEE Power and Energy Society General Meeting; 2012. pp. 1–6.
- [46] Ghofrani M., Arabali A., Etezadi-Amoli M., Fadali M.S. Smart scheduling and cost-benefit analysis of grid-enabled electric vehicles for wind power integration. IEEE Transactions on Smart Grid. 2014; 5 (5):2306–2313.
- [47] Ghofrani M., Arabali A., Ghayekhloo M. Optimal charging/discharging of grid-enabled electric vehicles for predictability enhancement of PV generation. Electric Power Systems research. 2014; 117:134–142.
- [48] Schuller A., Hoeffler J. Assessing the impact of EV mobility patterns on renewable energy oriented charging strategies. Energy Procedia. 2014; 46:32–39.
- [49] Gottwalt S., Schuller A., Flath C., Schmeck H., Weinhardt C. Assessing load flexibility in smart grids: Electric vehicles for renewable energy integration. In: IEEE Power and Energy Society General Meeting (PES); 2013. pp. 1–5.
- [50] Strnad I., Skrllec D., Tomisa T. A model for the efficient use of electricity produced from renewable energy sources for electric vehicle charging. In: Proceedings of 2013 4th International Youth Conference on Energy (IYCE); 2013. pp. 1–8.
- [51] Zhu L., Yu F.R., Ning B., Tang T. Optimal charging control for electric vehicles in smart microgrids with renewable energy sources. In: Proceedings of IEEE 75th Conference on Vehicular Technology Conference (VTC Spring); 2012. pp. 1–5.
- [52] Mets K., De Turck F., Develder C. Distributed smart charging of electric vehicles for balancing wind energy. In: Proceedings of IEEE 3rd International Conference on Smart Grid Communications (SmartGridComm); 2012. pp. 133–138.

- [53] Pantoš M. Stochastic optimal charging of electric-drive vehicles with renewable energy. *Energy*. 2011; 36:6567–6576.
- [54] Tushar M.H.K., Assi C., Maier M., Uddin M.F. Smart microgrids: Optimal joint scheduling for electric vehicles and home appliances. *IEEE Transactions on Smart Grid*. 2014; 5:239–250.
- [55] Fazelpour F., Vafaeipour M., Rahbari O., Rosen M.A. Intelligent optimization to integrate a plug-in hybrid electric vehicle smart parking lot with renewable energy resources and enhance grid characteristics. *Energy Conversion and Management*. 2014; 77:250–261.
- [56] Battistelli C., Baringo L., Conejo A. Optimal energy management of small electric energy systems including V2G facilities and renewable energy sources. *Electric Power Systems Research*. 2012; 92:50–59.
- [57] Patil R., Kelly J.C., Filipi Z., Fathy H. A framework for the integrated optimization of charging and power management in plug-in hybrid electric vehicles. In: *Proceedings of 2012 American Control Conference (ACC)*; 2012. pp. 1327–1334.