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**碩士學位論文**

**考慮光伏發電不確定性的具有儲能係統和光伏系統的電動汽車充電站的能源管理策略**

***Energy Management Strategy for EV Charging Station with ESS and PV Considering PV Generation Uncertainty***

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Abstract

The current model of transmission and distribution of electricity has proven to be unreliable and inefficient. This is because the grid technology currently in use has changed very little since it was developed. An electric vehicle, photovoltaic-based charging station equipped with an energy storage system is proposed and an algorithm for economic dispatch of the controllable resources in such a station to overcome the grid shortage is presented. Mathematical models for a subsidy-free integration of photovoltaic and energy storage systems in a charging station are developed along with a blueprint for optimizing the contract capacity of the charging station.

A chance-constrained programming method is proposed on grounds of photovoltaic uncertainty to determine the optimal dispatched and contracted power from the utility, such that the charging cost of the electric vehicle is minimized. Simulations are conducted for a comparison with the existing method. Numerical results indicate that our proposed approach provides a range of contract capacity sizes that benefits both the aggregator of the charging station and electric vehicle users. We showed also how the vehicles could be reliable agents in supporting the grid when photovoltaic panels fail to be while minimizing their charging cost.

***Index Terms***—optimization, energy storage system, charging station, renewable energies, vehicle-to-grid/grid-to-vehicle (V2G/G2V), confidence level, aggregator, chance-constrained programming

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Abbreviations

1. Indices

|  |  |
| --- | --- |
| *i* | The EV number. |
| *t* | Time instant. |

1. Parameters

|  |  |
| --- | --- |
| *M* | Total number of EVs in the station. |
| *x* | EV charging state, binary number, 1 if EV is charging, 0 otherwise. |
| *y* | EV discharging state, binary number, 1 if EV is discharging, 0 otherwise. |
| *Δt* | Time step size. |
| *α* | EV V2G agreement. |
| *p*max | EV maximum discharging power (kW). |
| *p*min | EV maximum charging power (kW). |
| *w*ess | ESS charging state, binary number, 1 if ESS is charging, 0 otherwise. |
| *v*ess | ESS discharging state, binary number, 1 if ESS is discharging, 0 otherwise. |
|  | ESS maximum charging power (kW). |
|  | ESS instantaneous state of charge. |
|  | ESS maximum SOC. |
|  | ESS minimum SOC. |
| *CC* | Contract capacity (kW). |
| *Price*cc | Contract capacity subscription price($/kW). |
| *S* | Charging priority order reference. |
| *N* | Maximum number of EVs in the charging station. |
|  | EV electricity buying price coefficient from the aggregator. |
|  | EV electricity selling price coefficient to the aggregator. |
|  | Aggregator wholesale electricity buying price coefficient from the grid. |
|  | Aggregator wholesale electricity selling price coefficient to the grid. |

1. Variables

|  |  |
| --- | --- |
| *SOC* | EV instantaneous state of charge. |
| *SOC*initial | EV SOC upon arrival. |
| *SOC*desired | EV desired SOC at departure time. |
| *SOC*min | EV minimum allowed SOC. |
| *SOC*max | EV maximum allowed SOC. |
| *cap* | EV battery capacity (kWh). |
| *BatCost* | Battery cost ($). |
| *BDC* | Battery degradation cost ($/kWh). |
| *Price*charge | Charging electricity price ($/kWh). |
| *Price*discharge | Discharging electricity price ($/kWh). |
| *t*a | Individual EV arrival time. |
| *t*d | Individual EV departure time. |
| *t*start | First EV arrival time. |
| *t*end | Last EV departure time. |
| *p* | EV scheduled power (kW). |
| *P*ess | ESS output power (kW). |
| *C*ess | Proportion of maximum power supplied to ESS considering contract capacity. |
| *η*ess | ESS scalability factor. |
|  | ESS remaining capacity ignoring its minimum SOC. |
|  | ESS remaining capacity including its minimum SOC. |
| *γ*ess | Fraction of ESS power sold to the grid. |
| *P*PV | PV output power (kW). |
| *θ* | Confidence level in predicting PV output power. |
| *P*ess | ESS output power (kW). |
| *β*PV | Fraction of PV power sold to the grid. |
| *ΔP*PV | PV power discretization step size. |
| *L*PV | PV power discretization length. |
|  | Mean value of the collected PV power (kW). |
| *σ*PV | Standard deviation of the collected PV power. |
| *P*Load | Load power consumption (kW). |
|  | Mean value of the collected load power consumption(kW). |
| *σ*Load | Standard deviation of the collected load power consumption. |
| *Sat*EV | Number of EVs reaching their desired SOC. |
| *Cost*EV | Total aggregated EVs charging cost ($). |
| *λ* | Exterior penalty factor. |
| *p*grid-request | Grid requested power from the station (kW). |
| *p*station-grid | Power delivered to the grid from the station (kW). |
| *𝜏*charge | Charging priority index. |
| *𝜏*discharge | Discharging priority index. |
| *K* | Charging priority order. |
|  | Computed cost index for a given contract capacity size. |
|  | Minimum value of the computed cost indices for a given contract capacity size. |
|  | Maximum value of the computed cost indices for a given contract capacity size. |
|  | Computed utility for a given contract capacity size. |
|  | Minimum value of the computed utilities for a given contract capacity size. |
|  | Maximum value of the computed utilities for a given contract capacity size. |
|  | Aggregator total profit. |
|  | Aggregator profit from selling electricity to EVs. |
|  | Aggregator profit from selling EVs electricity to the grid. |
|  | Aggregator profit from selling ESS electricity to the grid. |
|  | Aggregator profit from selling PV electricity to the grid. |

1. Functions

|  |  |
| --- | --- |
| *f* | Main objective function. |
| *f*cc | Contract capacity optimization objective function. |
| *f*UCA | Uncoordinated charging algorithm objective function. |
| *f*BCA | Brute charging algorithm objective function. |
| *f*arrival | EV arrival time probability density function. |
| *f*Load | Load power consumption probability density function. |
| *f*PV | PV power output probability density function. |
| *Pr*PV | PV power output probability mass function. |
| *G*PV | PV power output cumulative density function. |
| *H* | Heaviside function. |
| *norm* | Min-max normalization function. |
| *I*EV | Total aggregated EVs charging cost index function. |
| *I*Agg | Aggregator cost index function for subscribing to contract capacity. |
| *U*Agg-EV | Aggregator and aggregated EVs utility function. |

1. Introduction
2. Background and Motivation

When we use electricity, we rarely think about how it works. All we know is that when we flick a switch or press a button, our lights turn on, our ovens heat up, and our televisions broadcast our favorite shows. What goes on behind the scenes is that power is generated at a power plant, and then transferred to substations so that transformers can turn it into usable electricity. From there, electricity is sent to our homes and places of work through a series of power lines and wires. A common name for this process is the grid.

Each day, the utility grid needs to supply us with what is known as the baseline. The baseline is the amount of electricity the utility grid needs to produce. In addition to the baseline, the utility grid also needs to handle sharp increases in energy consumption. For example, electricity usage tends to spike in the evenings when people come home from work. In the summer months, air conditioners that run all day also have a significant impact on the grid. These types of situations are what the industry calls peak usage times.

Peak usage times have a significant impact on the grid. To compensate, the industry needs plans to reduce the load to prevent transmission glitches, extreme heat, and the heavy costs associated with each. Demand response is one of the solutions to this problem.

Demand response allows customers to voluntarily cut back on their electricity consumption during defined hours, specific days of the week, at times where the cost is high, or in emergencies such as blackouts. With the increase of electric vehicles adoption as an alternative to fuel vehicles, the grid can benefit from their flexibility.

In fact, the electric vehicle charging period could easily be shifted to different times or even curtailed if it is not going to be used anytime soon. The increase of electric vehicles anytime does not impact the grid loading due to its flexibility. What if demand response fails to maintain the grid power reliability? Simply put, after shifting or curtailing the load on the customer side, the dispatch of the utility grid still can’t meet the needs of its entire customers. The industries are growing so fast, electricity has become the cornerstone of the modern development: action needs to be taken at all levels of society without delay to find a concrete solution to the challenges we face.

The second solution to mitigate the impacts of the incredible increase in load consumption on the grid is energy arbitrage. Energy arbitrage is the practice of purchasing electricity from the electricity grid when it is cheap and storing it for later use when the utility grid electricity is expensive. The utility grid does not increase the electricity price arbitrary because of greediness but to deter users from reducing their consumption when the demand becomes significant for fear of not being able to satisfy the overall electricity consumption.

Back on energy arbitrage, the concept is similar to storing solar energy for later use but here it's about charging a battery with energy from grid rather than solar panels: time-variant electricity pricing is the core of the concept. The main idea is to save money for self-use, but with the grid, in need, the energy stored in the battery could be sent back to the grid in exchange for payment.

The emerging of the new technology vehicle-to-grid along with stationary energy storage systems and photovoltaics could be a huge support to the grid. The grid could manage efficiently the shortage due to the increase in load consumption. Since electric vehicles are used for a daily routine they can’t be treated as stationary energy storage. The most effective way to avoid an undesirable situation such as the inability to have sufficient energy in one’s electric vehicle battery to cover one’s trip is establishing a charging station with a smart agent named aggregator to coordinate the system electric vehicles, photovoltaic, energy storage system in a manner to support the grid when needed but also guarantee a minimized charging cost for vehicles users and meet their needs.

The entire society benefits from the strategy created and put into action by the aggregator of the charging station. As for the electric vehicles, reducing their charging cost is the key factor to encourage society to give up on fuel vehicles to the detriment of electric vehicles.

Let's the world as a whole move hand in hand toward clean energy and smart grid to ensure a safe, healthy, and pleasant environment for future generations.

1. Literature Review

The electric power industry considers demand response programs as an increasingly valuable resource option whose capabilities and potential impacts are expanded by grid modernization efforts. These demand response programs have the potential to help electricity providers save money through reductions in peak demand and the ability to defer the construction of new power plants and power delivery systems. With the increases of electric vehicles (EVs) studied have shown how electric EVs could be integrated into the demand response program to support the grid.

F. Rassaei et. al. [1]showed that EV could effectively be used as demand response agent and still satisfy their charging requirements. R. Yu et. al. [2] demonstrated that the real EV mobility can balance the power demand among districts and improve the demand response management performance in vehicle-to-grid(V2G) mobile energy networks. The study carried out by R. Yu et. al. [2] has proved the fact that EV is not being used only as a controllable load but also as storage to provide ancillary services to the grid.

The ancillary services include the provision of reactive and active power. A direct illustration is found in the research done by A. Y. Lam et. al. [3] where they modeled an aggregation of EVs with a queueing network, whose structure helped estimating the capacities for regulation-up and regulation-down separately.

The new concept consisting of the injection of energy to the grid through V2G technology is a trending topic there is a need for a central aggregator to manage the charging of EVs in the charging station (CS). Instead of relying only on EVs whose stay in the charging station may be short leading to their incapacity to provide V2G services, the CS needs additional entities at all costs to fulfill the grid request. One possible solution suggested by M. Nehrir et. al.[4] is the use of an energy storage system (ESS) along with photovoltaic (PV) to make hybrid energy systems (HESs) for smart grid applications.

In the literature, different approaches to integrate PV, EVs and ESS in a CS have been investigated in depth. Most of them are not practical because they tend to make use of PV and ESS for charging vehicles. To make their strategies work properly a subsidy is needed. K. Chaudhari et. al. [5] for example, focuses on analyzing subsidy needed to economically deploy the PV system near the EV CS along with ESS as the costs for PV and ESS are still rather high. Their proposed strategy on integrating PV, ESS and EV is unfeasible as in current time there is insufficient subsidy worldwide to trade self-installed energy sources with EV, instead the trade with the grid is the way to go.

L. Yao et. al[6] through extensive simulations show that using PV and ESS for charging EVs, the satisfaction of the latter is maximized but they ignore completely the satisfaction of the aggregator of the CS. J. Pascual et. al. [7]proposed a strategy that makes use of forecasted power profiles in order to eliminate the lag in the grid power profile. Their strategy does not involve EV but at least makes sense as it suggests the use of ESS and PV for grid support.

After adopting the proper charging strategy, the aggregator needs to choose an optimization tool to maximize his/her profit as well as minimize EVs charging costs. Different methods are been used. C. Jin et. al.[8] used the Lyapunov optimization technique to reduce EVs charging cost and their mean delay time of fulfilling their charging requests. EVs were mainly charged with wind power first, then the power drawn from the grid.

Impacts of renewable energies have been investigated in the research of R. Wang et. al. [9]. The results obtained via quadratic programming showed that their proposed EV charging scheme has a good performance in enhancing the system fault tolerance against uncertainties and the noises of real-time data. Their work focused more on improving the prediction error of renewable energy which is different from the confidence level one may have with a predicted value.

Basic mixed-integer programming helped W. Tushar et. al. [10] showing that uncertainty in PV generation can be effectively compensated, along with the minimization of the total cost of energy trading to the CS, by integrating more green EVs. In fact, green vehicles are the more environmentally friendly vehicles and thus assist the CS to reduce its cost of energy trading by allowing the CS to use their batteries as distributed storage. The other two types of charging schemes namely the premium and the conservative schemes, EVs are interested only in charging their batteries, with noticeably higher rates of charging for premium EVs. Those EVs battery could not be used for V2G services.

Real-time management of CS is implemented by A. Mohamed et. al. [11]using fuzzy logic. Various time-consuming evolutionary methods have shown satisfactory results for EVs scheduling.

H. K. Nunna et. al.[12] by the means of bee colony proposed a novel bidding strategy for PEVs offering V2G by including the projected battery degradation cost to integrate them into microgrid operation. R. Mehta et. al[13] through a genetic algorithm (GA) showed that their proposed integrated grid-to-vehicle (G2V) and V2G charging approach improved the penetration of EVs within a workplace car park. An improved particle swarm optimization used by P.-f. Zhang et. al. [14] seem to converge faster and their proposed charging strategy can make a great profit improvement for the parking lot. The proposed model of the EV parking lot is located nearby the commercial office buildings. The optimization methods mentioned above are so slow for real-world applications.

Nowadays, the widely used optimization methods for EVs scheduling are linear programming (LP), mixed-integer linear programming (MILP)and binary linear programming (BLP). For instance, Sarabi, S. et. al. [15] implemented the scheduling of 20 EVs in a railway station parking lots based on BLP; however, ESS and PV systems were not considered in the problem. Jin et. al. [16] maximize the revenue of the aggregator of a CS by the mean of MILP. Tushar et. al. [10]on the contrary, focus on minimizing the charging cost of EV using MILP.

M. Ş. Kuran et. al.[17] maximize both the revenue and EV users’ satisfaction thanks to LP. With the same solver, Jin et. al.[18] maximize aggregator’s profit on one hand, on the other hand, minimize EV user’ charging cost. In the same vein, Gao et. al.[19] maximizes the overall operation cost of a CS.

Deterministic methods like LP cannot solve problems involving uncertainties such as PV prediction errors. Chance-constrained programming is a method that can take into account uncertainty. Both B. Wang et. al[20] and H. Liu et. al [21] showed that a chance-constrained method could be used effectively in battery swapping stations(BSS) scheduling.

1. Research Method and Contribution

In this present study, we present the optimization solution for minimizing the cost of charging for EV owners by using PV and ESS to maximize the profits of the CS. This algorithm can be used for EV CS management; the connection between vehicles and the grid is bidirectional, which allows the vehicles to operate as aggregated loads, distributed storage units, or standalone energy sources.

The proposed strategy is realistic because we do not consider any subsidy in the deployment of PV and ESS in CS. The contributions of this paper are as follows:

* First, we designed a concise blueprint with a utility function that considers both aggregator and EV’s satisfaction to determine the optimal contract capacity needed for a given CS. The proposed method is practical as it needs a lengthy Monte Carlos simulation to come up with statistical data that can guide decision-makers.
* Second, we suggested that PV and ESS be used first for the facility's basic need then sold to the grid. EV is our priority during charging periods, then ESS. During the exchange of energy with the grid that priority is inversed. The charging of EVs and ESS are done simultaneously.
* Third, we made a comprehensive study in which we infer into the predicting value of PV output power by considering different levels of confidence. We made the use of V2G win-win cooperation where EVs minimize their charging cost while the aggregator reduces the risk for not being able to provide the amount of power requested by the grid due to PV uncertainty. To solve the optimization problem with uncertainty, we used chance-constrained programming along with LP. The existing methods related to chance-constrained programming are essentially for BSS. This paper is the first to apply the aforementioned method to coordinate the scheduling of EVs, ESS, and PV in a CS.
* Finally, we explored the influence of the V2G program on the aggregator profit. The idea was to find a minimal level of acceptance of the V2G program to incite aggregator upgrading the charging station infrastructure, that’s, replace the unidirectional chargers with the bidirectional one.

1. Organization of the Thesis

The remaining of this paper is organized as follows: Chapter 2 presents the overall system architecture for the EV bidirectional charging station. Chapter 3 describes the proposed EV charging optimization approach, followed by extensive computer simulations in Chapter 4. Chapter 5 presents conclusions and prospects.

1. System Architecture and Operational Flow
2. Introduction

In Chapter 2, the system architecture and the operation flow will be introduced. In Section 2.2, the overview of the data preprocessing stage is presented. We will show the sequence of events to be done before quicking out the charging station scheduling. In Section 2.3, the operation flow during the charging station scheduling is introduced.

1. System Architecture

The present study focuses on the scheduling of the aggregated EVs fleet, ESS, load, and PV simultaneously. To start the overall operation, data are preprocessed first.

The preprocessing stage is depicted in Fig. 2. 1. where the aggregator determines the optimal contract capacity for the EVs fleet, generates PV and load sample data. The optimal contract capacity for the EVs fleet was found by maximizing concurrently both the EVs fleet and the aggregator of the CS utility functions for a given set of contract capacities subscriptions. The maximization of the utility functions was run over 1000 monte Carlos simulations to fully capture the EV fleet behavior.

We collected load data and fitted them to a normal probability distribution function (PDF). The obtained PDF is then used to generate sample load data for further use. It is noteworthy to mention that a load of a building is controllable, its prediction values have been assumed

|  |
| --- |
|  |

Fig. 2. 1. Data prepossessing schematic of the proposed EV charging station scheduling strategy.

certain in the current study.

As for the PV, its prediction is strongly related to weather conditions. To consider the impact of PV prediction error, we generated PV sample data considering different confidence levels.

1. Operational Flow

From the preprocessing stage, we get to the main scheduling stage. The scheduling operation flow is described in Fig. 2. 2. Aggregator coordinates the scheduling operation. EVs and ESS are charged first from the grid. The grid also supplies the energy to the system-building load which is primarily served by ESS and PV.

During high electricity prices, a power request from the grid leads the aggregator to set up a strategy to maximize the trade profit with the grid. The trading strategy stipulates that PV and ESS are the first contingents to sell power to the grid. In case the grid request exceeds what the two can provide, EVs are used to fill the gap while making sure they can get their desired state of charge (SOC) on time.

|  |
| --- |
|  |

Fig. 2. 2. Schematic of the proposed EV charging station scheduling strategy.

1. Proposed EV Charging Optimization Approach
2. Introduction

This thesis proposes an optimal scheduling method for a large EV charging station PV-based equipped with ESS. The optimal strategy not only yields more profit for the aggregator of the CS by using EVs, ESS, and PV but also achieves a minimized charging cost for EV. In addition to the financial aspect, this thesis also investigates the impact of PV generation uncertainty on the amount of power that can be discharged by EVs to meet the grid request.

Another subsequent work explored is the minimal V2G penetration level needed to make the aggregator upgrade the charging station infrastructure from unidirectional chargers to bidirectional ones.

Those contributions have never been done by any thesis or papers, so undoubtedly it is a milestone both in the field of EV scheduling.

In Section 3.2, the present charging station scheduling objective function is presented. The objective function has many constraints to be considered. Section 3.3 gives more details on the validity of the constraints used for any CS scheduling.

Section 3.3 focuses more on the exchange of energy between the grid and the charging station. A blueprint for choosing the right contract capacity is proposed in section 3.5 while section 3.6 presents the

load and PV power processing.

1. Objective Function

The total cost is defined as the sum of the charging costs over the charging time horizon. The scheduling optimization problem comprises minimization of the total cost of charging and discharging EVs during their stay. The optimization involves the relationship between ESS in an interval and the charging power of an individual EV, instant energy constraints, final energy constraints, lower bound, and the upper bound of the charging power. Mathematically, the optimization problem can be formulated as (3.1) .

|  |  |
| --- | --- |
|  | (3.1) |
|  | (3.2) |

The decision variables , , , , and denote EV charging status, EV discharging status, ESS charging status, ESS discharging status, the power drawn of each EV in every time slot during EV stay in the station and ESS charging feasibility, respectively. The total number of EVs in th CS at scheduling ime instant is M. The scheduling covers the time intervall from the entrance time of the first EV in the CS noted *t*start to the exit time of the latest EV from the CS which departure time is denoted by *t*end. is the scheduling time step, the smaller the more accurate the scheduling is but time-consuming as well from the solver used side.

The battery degradation cost *BDC* in (3.2) is obtained from A. Aldik et. al. [22] publication where a linear model is proposed to find the relationship between the battery degradation cost and the battery cost *BatCost*.

The objective function is to minimize the total net cost of charging vehicles, maximize V2G, PV power sale, and ESS usage. The formulation has four components:

* The cost of buying energy from the grid *Pricet*charge is based on energy prices. Energy is purchased preferably when the grid offering price is low. Assuming a given EV stays in the CS and electricity price remains the same, that EV is charged right away without any optimization. A similar operation is performed for EV not having enough time to get their desired SOC.
* ESS is charged with the amount of poweronly when the energy price *Pricet*charg*e* is low, and it is the unique strategy to generate profit from the stationary battery when selling power back at the rate *Pt*ess to the grid at higher energy price *Pricet*discharge.
* V2G essentially considers the EV owner’s consent to join the V2G service or not. The consent is denoted by.
* The amount of PV and ESS to be sold to the grid derived from their respective instantaneous power  and is decided by the aggregator through parameters and  . The remaining 1-, 1- of PV and ESS, respectively, are given to the local load. In this thesis, the load constituted the lighting and other basic needs of the station. The energy required by the load can then be easily satisfied by using ESS and PV cells.

In the optimization problem, the objective function is convex, and all the constraints functions are linear. Due to the parameter *θ* used as the confidence level in estimating PV output power, the method accurate to solve problems with uncertainty is chance constrained-programming. We used linear programming as the deterministic solver in the present chance constrained-programming. The solution to the optimization problem provides the optimal scheduling scheme for EV charging and discharging during the day.

1. Constraints
2. SOC Constraints
3. Generic SOC Constraints

The SOC is defined as the electrical energy in an EV battery at a specific instant time. The inverter rating power of the battery and its allowed SOC are the commonly used constraints for EV scheduling. Regardless of the algorithm to be adopted, the charging power of the battery should not exceed the threshold, named as **for the *ith* EV. Bidirectional flow allows discharging for a certain limit **.

Arbitrary we defined the charging power to be negative value, the discharging to be positive in this paper. The upper bound and the lower bound of the charging/discharging power is shown in (3.3).

|  |  |
| --- | --- |
|  | (3.3) |

The charging of EV is expected to start as soon as it arrives at the station and stop right before EV leaves the station as illustrated in (3.4) where and are respectively the arrival and the departure time of the *ith* EV. Both the charging status  and the discharging status  of the *ith* EV are equal to zero when the *ith* EV is outside of the CS.

|  |  |
| --- | --- |
|  | (3.4) |

During its stay, EV (3.5) as well as ESS (3.6) cannot charge and discharge simultaneously. In (3.6)and are respectively the charging and the discharging status of the stationary battery ESS.

|  |  |
| --- | --- |
| For EV | (3.5) |
| For ESS | (3.6) |

Giving that the maximum of the inverter power may not be used to charge a battery if the latter is almost full, the maximum allowable SOC named should be known in advance for any given *ith* EV.

Alike the maximum SOC, there is a limit in discharging a battery, called minimum SOC noted . Therefore, the following equation(3.7) should hold for a given battery:

|  |  |
| --- | --- |
|  | (3.7) |

In addition to the aforementioned constraints, at departure, EV is expected to have its desired SOC labeled as , fulfilling a given *ith* user demand having the proportion  of its total capacity  when arriving in the CS. Equation (3.8) is used to illustrate user demand satisfaction.

|  |  |
| --- | --- |
|  | (3.8) |

1. SOC Constraint Linearization

Numerical optimization of general nonlinear multivariable objective functions requires efficient and robust techniques. Efficiency is essential because these problems require an iterative solution procedure, trial and error are impractical for more than three or four variables. Robustness (the ability to determine an optimal solution) is desirable because a general nonlinear function is unpredictable in its behavior; several relative minima may occur. In some regions, the optimization algorithm can evolve very slowly toward the optimum, requiring excessive computation time.

A reliable charging station is expected to perform scheduling within 5 min of the arrival of the EV and account for the owner’s random behavior until the departure time. Constraints exhibited by evolutionary techniques such as genetic algorithm, differential evolution (DE), particle swarm optimization, and bee colony used by Nunna et. al.[12], Mehta et. al.[13] and Zhang et. al.[14] are time-consuming.

The time burden can be solved by linearizing the SOC constraint of the EV battery. Basing on Sarabi et. al[15] work, LP can be used to accurately determine the minimum cost for charging EV.

In this present study, instead of just describing LP like Turker et. al.[23], a well-structured linearization approach is proposed. By definition, the SOC is defined as follows for any instantaneous instant time *t*:

|  |  |
| --- | --- |
|  | (3.9) |
|  | (3.10) |

Replacing **from (3.9) by its expression in (3.10), we obtain the following expression:

|  |  |
| --- | --- |
|  | (3.11) |

We now present the generalized equation of the SOC constraint in a compact form using the aforementioned deductions. The generalization considers the cumulative constrained power exchanged between the grid and a given vehicle within a specified interval of time.

By an immediate recurrence, we obtain the following expression:

|  |  |
| --- | --- |
|  | (3.12) |

The relationship between the SOC and the cumulative power developed in (3.12) is used to impose some constraints on the cumulative power to avoid battery capacity limits violation. Recalling inequality (3.7) and inserting (3.12) in (3.7):

|  |  |
| --- | --- |
|  | (3.13) |

Thus, the following useful constraint (3.14) derived from (3.13)is obtained for writing the format *Ax ≤* *b* of LP.

|  |  |
| --- | --- |
|  | (3.14) |

The aforementioned constraints are only applicable to ESS because it is not expected to have a specific SOC at the end of the day: profit maximization is the main target. In addition to these constraints, the cumulative energies stored in the EV battery must be equal to the desired SOC of the customer when leaving the station. The equality constraint *A*eq *x* = *b*eq of LP is devised as follows using equation (3.8):

|  |  |
| --- | --- |
|  | (3.15) |
|  | (3.16) |

1. ESS Charging Feasibility
2. Contract Capacity Acknowledging

A major constraint of a CS is its contract capacity(CC), namely the maximum charging power. An ideal CS operates within 1%–90% of its capacity and still charge the ESS. Beyond a certain threshold, an estimate of the amount of power from the grid to be purveyed to ESS makes the CS the subject of smart scheduling. The coefficient established in (3.17) denotes the proportion of the maximum power to be supplied to the ESS considering the contract capacity. The expression for is given below as:

|  |  |
| --- | --- |
|  | (3.17) |

1. ESS Capacity Limits

Another non-negligible and straightforward parameter to consider in ESS scheduling is its previous SOC. A full ESS need not need to be charged. Furthermore, a nearly full ESS requires very little power depending on the constraint imposed by the contract capacity. For an empty battery, the maximum power is the desired charging. With respect to the possible mentioned eventualities, fraction  is calculated to adjust the maximum power of ESS where and  are respectively the maximum and the previous SOC of the ESS.

|  |  |
| --- | --- |
|  | (3.18) |

A flat battery compared to a battery discharged to a certain tolerance, namely **,lasts the least. A. Hoke et. al.[24] , A. Brissette et. al.[25] and M. Ortega-Vazquez et. al.[26] showed that a deep discharge reduces considerably the battery cycle of life. Given this additional information,  is derived from  to include ** as follows:

|  |  |
| --- | --- |
|  | (3.19) |

The two previously mentioned proportional coefficients (3.17) and (3.19) together constitute the scalability factor of ESS, as depicted in(3.20).

The scalability factor is a value between 0 and 1. The incapacity to charge ESS is denoted by **. For a nonzero value of **, ESS is settled to receive energy from the grid depending on the current grid offering energy price. If the CS operates under the contract capacity, **becomes 1, revealing the possibility to charge ESS at its power rating.

Thus, if the maximum capacity is reached, the first term  is equal to zero, the second term need not be checked. We infer that ESS cannot be charged, too many vehicles are present in the station. If the number of EVs in the station is less, then the first term Cess is evaluated to a value close to 1 exempting the charging of the ESS from the contract capacity constraint. The second term  expresses the constraints emanating from the battery minimum SOC and its maximum SOC, allowing permissible energy flow between the ESS and grid.

In short, the scalability factor **adjusts the amount of ESS maximum charging power available for its charging by considering both the contract capacity constraint and the battery inherent limits simultaneously.

|  |  |
| --- | --- |
|  | (3.20) |

1. Contract Capacity Constraint Exemption
   * + 1. Charging Priority

EVs are expected to be widely used soon. Therefore, EVs CS should be able to charge hundreds of EVs. Contract capacity is the constraint. At the peak time, with the high penetration of EV, the transformer is likely to be overloaded if all EVs have the same behavior, either charging or discharging, simultaneously.

Smart scheduling becomes necessary to coordinate the charging of the entire fleet. Modified electricity price patterns were used to shift the charging periods. Those patterns were assigned according to a fair and concise method, unlike H. Zhang et. al. [27] proposed a priority method, where the priority of the EV is determined by two ambiguous steps.

A nearly full EV is set to have low priority, leading to its charging delay. By contrast, EV leaving soon should be charge as soon as possible by keeping it in a high priority group. The charging priority is defined in (15) as *τt*charge encompassing the *ith* user expected SOC at departure as well as the previous instant time SOC of the battery and the given departure time . The smaller the index, the higher is the priority.

|  |  |
| --- | --- |
|  | (3.21) |

* + - 1. Time-of-use Patterns Assignment

The charging priority index *τt*charge was used to classify EVs. The smallest priority index was assigned order 1. The priority indices are ranged from 1 to *M*. Equation (3.22) is an arithmetic progression with common difference of *d*, set to 1 for preference. The priority order table is computed as in Fig. 3. 1. (a).

|  |  |
| --- | --- |
|  | (3.22) |

where *m* is the starting index, *n* is any index (*n ≥ m),* *km* is the first term of the arithmetic progression, and *S* is defined in (3.23) as the number of vehicles leading to the transformer overloading.

|  |  |
| --- | --- |
|  | (3.23) |

For simplicity, we considered the extreme situation where vehicles are being charged with their maximum charging power . The equation yielding *S* is shown in (3.24) where *CC* is the contract capacity power size.

|  |  |
| --- | --- |
|  | (3.24) |

Here, *S* is used when the number of vehicles exceeds the number of EVs aggregator can freely assign the maximum power to each. EV whose priority order is higher than the threshold *S* are assigned patterns 2 and 3 as shown in Fig. 3. 1. (b). EV with priority below the threshold *S* is assigned pattern 1.

The time-of-use (TOU) rate plan was used in determining the charging EV electricity consumption. TOU is a sliding rate scale, structured according to the peak and off-peak times of the day. Under such a plan, the EV bill was calculated using the amount of energy EV charges/discharges.

The standard TOU was modified for the following reasons. For illustration, assuming having three vehicles A, B, C which can charge during the lower prices divided in three time periods T1, T2, T3. Without the modified TOU, all the three vehicles charge at the period T1 and congestion may rise as they are charging at the same time. To avoid this eventuality, the modified TOU assigned for instance, EV A to the time period T1, EV B to T2, and EV C to T3.

As shown in Fig. 3. 2. (a) pattern 1 is the most profitable and is assigned to the first vehicle entering the charging station. This pattern allows charging at the beginning of the lower electricity price periods. Pattern 2 depicted in Fig. 3. 2. (b) is the next profitable pattern to be assigned. This pattern allows charging in the middle of the low electricity period. The least profitable among these three patterns is pattern 3 shown in Fig. 3. 2. (c). Vehicles in this pattern are served the last.

The modified TOU is used for scheduling purposes. It does not increase the charging cost and only allows us to have control over the charging and discharging periods with LP solver.

|  |  |
| --- | --- |
| (a) | (b) |

Fig. 3. 1. (a) Priority order table, (b) TOU pattern assignment.

|  |
| --- |
| (a) |
| (b) |
| (c) |

Fig. 3. 2. Revised TOU: Patterns (a) 1, (b) 2, and (c) 3.

1. Energy Exchange with Grid
2. Exchange Strategy

PV and ESS were installed to support the local load demand, reducing dependency on the grid. A sunny day may result in a high generation of solar power. The surplus power is sold to the grid or stored in the ESS. The aggregator of the CS is responsible for setting *β* of PV. When PV and ESS could not provide the power requested to the grid, power drawn from EV adherent to V2G is dispatched to address the shortage as described in (3.25) following a discharging priority  where *H* described in (3.26) is the Heaviside function.

EV with higher SOC and not close to their departure time is assigned higher priority, given by the formulae (3.27). The higher the index, the higher is the priority. It’s noteworthy to mention that 50% of the aggregated PV and ESS power is always given to the load when required.

The main constraint used in this section while solving the objective function (3.1) is shown in (3.28). Since the inequality (3.28) includes PV power which is estimated with certain confidence level  , the problem is solved by chance-constrained programming.

|  |  |
| --- | --- |
|  | (3.25) |
|  | (3.26) |
|  | (3.27) |
|  | (3.28) |

1. Profit Assessment

The aggregator of CS purchases the electricity from the grid at a wholesale rate, as well as selling it to the grid according to Z. Yang et. al. [28]works. Meanwhile, the EV user buys or sells electricity at a general price as individuals. Therefore, four price coefficients are set to describe the prices for EV users and the aggregator buying and selling electricity. Those four coefficients are defined as follows:

*  means EV user charges the electricity from the grid, then  is equal to 1, as the EVs act as individual customers.
* means EV user discharges the electricity to the grid.
*  and  mean the aggregator charges electricity or discharges energy, respectively.

Normally,  is less than or equal to  since aggregator buys electricity at a wholesale price. is less than or equal to  because the aggregator has the ability to sell a large amount of electricity to the grid according to its demands, while an EV user just sells quite a little electricity to the aggregator as an individual at random periods of time.

The profit generated from exchanging energy with the grid is composed of three sub profits: profit from EV, PV, and ESS. The profit from EVs is the electricity price gap by exchanging the power between the EVs and the grid. The profit from EVs can be divided into two subparts: the charging profit shown in (3.29) and the discharging profit (3.30).

The two other profits are shown respectively in (3.31) and (3.32). In (3.31) the profit from ESS is assessed using the TOU. PV is only for sale, so higher PV output is equivalent to higher profit from PV as mentioned in equation (3.32).

The overall aggregator profit is shown in equation(3.33).

|  |  |
| --- | --- |
|  | (3.29) |
|  | (3.30) |
|  | (3.31) |
|  | (3.32) |
|  | (3.33) |

1. Optimal Contract Capacity

The contract capacity is the binding contract signed by the aggregator and paid monthly used for charging the electric fleet. Subscribing for higher contract capacity is advantageous from the EVs point of view as they can reduce considerably their charging cost. From the aggregator standpoint, unused capacity is a waste, it’s more necessary than ever to find a method to estimate the optimal contract capacity.

Thus, we generated 1000 EVs data and evaluated them on a set of contract capacities. For each set of contract capacities, the cost indices are evaluated from both aggregator and EVs fleet postures. We used the objective function (3.34) where an external penalty function is used to avoid exceeding the maximum contract capacity subscribed for finding the minimal charging cost of the EVs fleet. The penalty parameter *λ* is adjusted minutely to get the feasible solutions that meet the contract capacity constraint.

The optimal minimized cost noted as  (3.35) found from solving the objective function (3.34) is squared to reflect the sensitivity of users toward their charging cost for later use in determing the cost index of EVs fleet. we also added the number of EVs satisfied (3.36) which acts as a heavy penalty for contract capacity causing EV users not being able to have their desired SOC at their departure time. EV satisfied labeled as  is the one getting their desired SOC at departure time. The cost index of the EVs fleet labeled as described above is shown in (3.37) where the contract capacity purchase price is slightly neglected.

The overall cost is normalized using min-max normalization shown in (3.38). A cost index of 0 means a favorable contract capacity while 1 means undesirable contract capacity. By analogy with the EV cost index, aggregator subscription price to the contract capacity is squared (3.39) along with the number of satisfied EVs and their charging cost. The obtained index is named the aggregator cost index to reflect he/her sensitivity toward a higher purchase price for a given contract capacity size. Pricecc represents the purchase price for a given contract capacity size.

With the two cost indices, we evaluated the utility function  for the overall system using equation (3.40) where M, the total number of EV, is included. It is used as an offset value to avoid the equation to vanish when both cost indices are equal to 0. Finally, the utility is also normalized as shown in (3.40) and 1 reflect the most desirable contract capacity utility value.

|  |  |
| --- | --- |
|  | (3.34) |
|  | (3.35) |
|  | (3.36) |
|  | (3.37) |
|  | (3.38) |
|  | (3.39) |
|  | (3.40) |
|  | (3.41) |

1. Probabilistic Model for Stochastic Variables
2. Probabilistic Model for Load Power Consumption

The load data collected online from [29] are fitted to a normal distribution as shown in (3.42). Each hourly data is assumed to follow the normal distribution  with mean  and standard deviation . As can be seen from Fig. 3. 3(a) the maximum load data is 20kW, and the load consumption seems to be continuous. The continuity illustrates a 24-7 service CS.

|  |  |
| --- | --- |
|  | (3.42) |

1. Probability Serialization Model for PV Generation
   * + 1. Probability Density Function

The PV data are collected from PV cells installed in a system building located in Changhua, Taiwan (R.O.C). Each hourly data is assumed to follow the normal distribution  with mean  and standard deviation  shown in (3.43). The PV power rating is 200kW, we collected the PV data from 6 am to 5 pm, there is no generation out of this time range.

The 12 PDFs are shown in Fig. 3. 3(b) where the maximum output power (200kW) is less likely to occur due to weather conditions. The charging station in the current study has two of the described PV, making altogether 400kW as the maximum possible PV generated power.

|  |  |
| --- | --- |
|  | (3.43) |

* + - 1. Probability Mass Function and Cumulative Distribution Function

The time-series multi-state probability sequence of PV power is constructed by using the PDF of PV output. The length of the multi-state probability sequence LPV is shown in (3.44)where the divisor ΔPPV is the discretization step size. The probability mass function (PMF) in (3.45) obtained by the integration of the PDF is used to evaluate the probability of generating a given PV power.

The piece-wise cumulative distribution function (CDF) in (3.46) is derived from the PMF. Using the CDF, we can get the PV output power (3.47) for a given confidence level by the means of the inverse of the CDF. The maximum PV output power is denoted by the confidence level of 1. It’s noteworthy to mention that the higher the confidence level the higher the predicted value is. For instance Fig. 3. 4.(a) shows a predicted PV data with a confidence level of 0.2. For a confidence level of 0.8 the obtained PV power shown in Fig. 3. 4. (b) is much higher than the one obtained in Fig. 3. 4. (a).

|  |  |
| --- | --- |
|  | (3.44) |
|  | (3.45) |
|  | (3.46) |
|  | (3.47) |

|  |
| --- |
| (a) |
| (b) |

Fig. 3. 3. PDF: load (a), (b) PV.

|  |
| --- |
| (a) |
| (b) |

Fig. 3. 4. PV Generation with confidence level: 0.2 (a), (b) 0.8.

1. Computational Results
2. Introduction

This chapter presents the simulation results of the proposed scheduling method to verify its performance and effectiveness. In Section 4.2, related parameters for simulations are introduced, including EV parameters, EV behaviors, ESS parameters. The CS parameters such as the contract capacity purchase price, the price coefficients set by the aggregator to make a profit from charging EV are given.

In Section 4.3, different charging methods are briefly introduced before providing the results obtained using those methods in section 4.4. The last section 4.4 presents the results of the overall topic covered in this thesis starting from the comparison between different EV charging methods.

To be more accurate on choosing the appropriate contract capacity size, the third part of section 4.4 assesses the range of optimum contract capacity sizes for different fleet sizes: 200, 400, and 500. Those optimum contract capacity sizes are used latter on to investigate the impact of PV confidence level on EV charging cost. The impact is expanded on the aggregator side in the following testing results to provide a deep economic analysis regarding the energy exchange between the grid and the CS. Finally, the influence of EV penetration on aggregator profit is verified by using different penetration levels.

1. Simulation Setup

To validate the effectiveness of the proposed algorithm, various numbers of fleet sizes of EV were investigated: 200, 400, and 500. A time window of 1440 minutes was considered in the CS scheduling. The scheduling time horizon is divided equally into *T* = 288 time slots of length Δ*t* = 5 minutes.

The maximum fleet size in our study is 500. We found the information on the EV arrival and departure time in similar research carried in Turkey by S. Guner et. al. [30]. The research was intended to find appropriate distribution functions to capture 500 EVs behavior. The vehicle data have been collected from Istanbul Parking Management Trade Inc. (ISPARK) statistics. Various distribution functions have been used; two-parameter Weibull distribution is found to provide reasonable performances for the arrival time while the departure time fits well to normal distribution. The corresponding Weibull distribution function *farrival* is shown in (4.1), with the two parameters *a* and *b*.

|  |  |
| --- | --- |
|  | (4.1) |

In fact, normal PDF is found to provide satisfactory results for the cars arriving during the morning bins (07:00- and 09:00 a.m.), which indicates that the cars arriving during the morning bins depart around 6.00 p.m. Those vehicles belong to the people who prefer using mass transportation (subway) to their works after parking their cars in the charging station. Therefore, those EVs park all day, up to the arrival of the owners by mass transportation. The mean for departure time PDF is set as 6pm and the standard deviation as 3 to illustrate different behaviors from various users.

|  |
| --- |
|  |

Fig. 4. 1. Arrival and Departure Time Data for 500 EVs.

Fig. 4. 1 shows both the generated arrival and departure time for 500 EVs used for the upcoming simulations. It’s noted the earlier EVs arrives in the CS around 4 a.m and the latest at 11 a.m. As for the departure time, the minimum value is 3 p.m whilethe maximum reaches 10 p.m maybe more since we are dealing with PDF.

The SOC of EV upon arrival is generated using a normal distribution with an average of 36% of the battery size and a standard deviation of 15% based on the SwitchEV project investigated by X. Chen et. al. [31]. The charging requirement of EV is set as 86% of the battery size as the mean and 14% as the standard deviation of its PDF. Information related to EVs behaviors is summarized in Table 4. 1 where the standard deviation of the normal distribution shown in Fig. 4. 2 and Fig. 4. 3 is expanded to capture diversity among users.

Additional details on the EV battery and the stationary battery specification are presented in Table 4. 2. EV battery capacity is 44kWh while for ESS we choose 500kWh. The former maximum charging power is -7kW and the latter is -100kW. The charging power and discharging power are assumed to be identical, just the flow direction is different.

Table 4. 1 Status of EVs

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variables | Distribution |  | Parameters | |
|  |  |  | a | b |
| Arrival Time | Weibull |  | 0.9831 | 16.8 |
|  |  |  | Mean | Standard deviation |
| Departure Time | Normal |  | 6:00 | 3 h |
| Minimum SOC | Normal |  | 12% | 8% |
| Maximum SOC | Normal |  | 94% | 5% |
| Initial SOC | Normal |  | 36% | 15% |
| Desired SOC | Normal |  | 86% | 14% |

Table 4. 2 Battery Specs

|  |  |
| --- | --- |
| Specs | Values |
| EV capacity(kWh) | 44 |
| EV maximum charging power(kW) | −7 |
| EV maximum discharging power(kW) | 7 |
| EV battery cost ($) | 8800 |
| EV battery degradation cost($/kWh) | 1.18 |
| ESS capacity(kWh) | 500 |
| ESS maximum charging power(kW) | −100 |
| ESS maximum discharging power(kW) | 100 |

|  |
| --- |
|  |

Fig. 4. 2. SOC minimum and maximum Data for 500 EVs.

|  |
| --- |
|  |

Fig. 4. 3. SOC initial and desired Data for 500 EVs.

The purchased cost of a new EV battery is taken as 8800$, which makes 1.18$/kWh as the battery degradation according to (3.2). As to the contract capacity price of the CS, it’s set to 7.5$/kW according to the monthly electricity bill of National Cheng Kung University.

In this thesis, it is assumed that the parking lot has sufficient charging spots to serve all the vehicles that arrive, some charging spots may be out of service due to the contract capacity threshold. Meanwhile, four electricity price coefficients are set as well as shown in Table 4. 3 to assess the profitability of the aggregator. For the price coefficients, we used the same setting as T. He[32].

The simulation is conducted in MATLAB Release 2018b, using the LP optimization solver. The specifications of the computer used for simulation were as follows: Intel i7 8700 CPU and 16 GB RAM.

Table 4. 3 Aggregator price coefficients

|  |  |
| --- | --- |
| Parameters | Values |
|  | 0.9 |
|  | 1 |
|  | 1 |
|  | 0.9 |

1. Comparing Different EV Charging Methods

The effectiveness of the presented charging algorithm was verified according to the methods presented in [33]. In the uncoordinated charging algorithm (UCA), the vehicle is charged upon arrival until it reaches the desired SOC. This approach is called first come, first served because the temporal price variation is not considered. The objective is to minimize the charging period of a given vehicle as suggested by A. S. Awad et. al [34] and not to exceed the contract capacity. The objective function is formulated using external penalty function (4.2) and easily can be solved both by a linear as well as a nonlinear optimizer.

|  |  |
| --- | --- |
|  | (4.2) |

The decision variables , , and *t* denote the charging status, the power drawn of each EV in every time slots during its stay in the station, and charging duration, respectively. In the brute charging algorithm (BCA), the temporal price variation is used for charging. In contrast to the uncoordinated charging, its effectiveness relies on long charging times.

This method differs from the proposed method since there is no V2G technology and only TOU pattern is used. The contract capacity power constraint is included directly into the objective function. The objective function is formulated as in (4.3) where EV charging cost is minimized for a day. The decision variables  and denote the charging status and the power drawn of each EV in every time slots, respectively, during the vehicles stay in the station.

|  |  |
| --- | --- |
|  | (4.3) |

The evolutionary algorithm is the third algorithm to be studied. Evolutionary algorithms have been used widely to schedule EVs charging. DE was used for comparison in the present study. The objective is the same as the proposed method. The V2G feature was disabled on both testing algorithms for a fair assessment.

In practice, DE did not allow us to implement the aforementioned constraint once the V2G feature is enabled. However, we successfully performed G2V because the minimum, maximum, and needed SOC are conserved after the mutation and crossover stage. The proposed method was compared with DE by looking at both the cost achieved and the simulation time by each method.

1. Simulation Results
2. EV Charging Methods Comparison

The uncoordinated method presented in [27] is set as the reference. The charging cost and algorithm speed were compared. We set large contract capacity sizes as shown in Table 4. 4 without any optimization. The next section provides an accurate blueprint for choosing the appropriate contract capacity size. The contract capacity size chosen for fleet size 200 is 1000kW, 1900kW for fleet size 400 and 2500 kW for the fleet size 500. The large contract capacity sizes exempt the compared methods slightly from the contract capacity constraint.

The first two algorithms, namely UCA and BCA were tested over their final total charging cost. Table 4. 5 lists the cost reduction achieved by the BCA. Owing to its V2G feature, the proposed method could achieve considerable cost reduction if the EV user adheres to the V2G program. On average, BCA achieved 19.2% of cost reduction while G2V/V2G with the proposed method cost reduction reached 29.6%.

In terms of the algorithm speed, all algorithms converged within the threshold of 5 minutes according to Table 4. 6 except the DE method. UCA was the fastest (30 s for 500 EVs) because it does not perform any scheduling. Then, BCA (44.9s for 500 EVs), which attempts to locate the charging period mostly during low charging price periods, was the next. This additional optimization feature makes it slower than the UCA method. The proposed method incorporating several intelligent features was the slowest but its computation time was acceptable because it was less than the time limit (5 min) imposed.

The random search–based optimization algorithm DE results in longer convergence time, especially with a large number of EVs the computational time is quite high. Table 4. 6 indicates that if the number of EVs is 500, the convergence time almost reaches the preset time slot, 5 min, thus resulting in no further execution of the commands by the Energy Management System (EMS) because the scheduling of the next turn is kicked off.

By contrast, the proposed method can not only improve the cost but also save approximately 85% CPU time, which is pivotal for real-world applications.

Table 4. 4 Charging Station Specification

|  |  |  |  |
| --- | --- | --- | --- |
| Fleet Size | 200 | 400 | 500 |
| Contract Capacity(kW) | 1000 | 1900 | 2500 |

Table 4. 5 Cost of Charging Using Different Algorithms

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Parameters | | Fleet size | | | Average |
| Performance | Method | 200 | 400 | 500 | - |
| cost ($) | UCA | 336.1 | 643.2 | 833.9 | 604.4 |
| BCA | 261.8 | 533.3 | 669.1 | 488 |
| DE | 281.2 | 555.9 | 688.5 | 508.5 |
| G2V only (proposed) | 258.5 | 517.1 | 659.4 | 478.3 |
| G2V/V2G (proposed) | 229.5 | 459 | 588.3 | 425 |
| Cost  Reduction  (%) | BCA | -22.1 | -17 | -19.6 | -19.2 |
| DE | -16.3 | -13.5 | -17.4 | -15.8 |
| G2V only (proposed) | -23 | -19.6 | -20.9 | -20.8 |
| G2V/V2G (proposed) | -31.7 | -28.6 | -29.4 | -29.6 |

Table 4. 6 Simulation Time

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Parameters | | Fleet size | | |
| Performance | Method | 200 | 400 | 500 |
| Time (s) | UCA | 15 | 23 | 30 |
| BCA | 20 | 31.5 | 44.9 |
| DE | 110.8 | 229.5 | 280.2 |
| G2V only (proposed) | 19.3 | 41.7 | 51.1 |
| G2V/V2G (proposed) | 22 | 43.1 | 56.7 |

1. Range of Optimum Contract Capacities

Basing on the PDF parameters provided in Table 4. 1, 1000 data on EVs are generated for Monte Carlos simulation. We compared it with an existing method from [35] used as a benchmark. The benchmark approach calculates the contracted power capacity size based on the hourly probabilities that EVs are connected with the power grid. The benchmark does not take account of the contract capacity purchased price for charging vehicles but rely only on EV penetration level. In our contract capacity optimization, the aggregator is involved.

In the process, we set the range of the contract capacity as 100kW-1400kW for the fleet size of 200. We noticed that the range 100kW-500kW led to a higher number of unsatisfied EVs and their cost indices were close to 1. Also, the range 1000kW-1400kW gave a cost index of 0 from EVs perspective but 1 from aggregator standpoint which means the chosen contract capacity sizes were too big and increased substantially the aggregator subscription price. We narrowed down the window to 500kW-1000kW.

According to the benchmark, the low-cost index for EV should be chosen that’s 883kW relying on Fig. 4. 4. Our approach shows that to consider aggregator satisfaction as well, any value from the range 722kW-883kW should be profitable to both.

It’s obvious from Fig. 4. 4 that the cost index for the aggregator keeps increasing as the contract capacity increases. On the contrary, the cost index for the EV fleet decreases substantially and is equal to 0 at 833 kW, stays at 0 for further increase in the contract capacity. Providing extra capacity no longer helps reduce the EV fleet cost index.

From Table 4. 7 considering the fleet size of 200 EVs it’s obvious that for smaller contract capacities the ratios of EVs having provided V2G are relatively low compared to larger contract capacities. For example, for 500kW as contract capacity, only 34% of EVs were able to provide V2G.

In contrast, as to the contract capacity of size 833kW, 52% of EVs were able to sell energy to the grid. The more vehicles provide V2G services the lower the charging cost is this is the overall point of Table 4. 7. The ratio of V2G EV increases with the increase of the fleet size basing on the results in Table 4. 8 which is about the fleet size 400 and Table 4. 9 for the fleet size 500.

Moreover, the tight contract capacities not only reduce the ratio of V2G but also forced certain vehicles to charge during higher TOU prices which increases considerably their charging cost but reduce the aggregator subscription price. The dilemma was to find the appropriate capacity to satisfy both the aggregator and the fleet. The aggregator-EV utility function according to Fig. 4. 4 has 3 maxima equivalent to the range of optimum contract capacities: 722kW-883kW.

By analogy, the fleet size 400 and 500 are treated as such. According to Fig. 4. 5, the optimum contract capacities lie in the interval 1622kW-1677kW for the fleet size of 400. It’s noteworthy to mention that for the contract capacity 1733 has an EV cost index almost equal to 0 but it’s not been chosen as its purchase cost index 0.65 is larger. Table 4. 8 provides more details on the reasons behind the choice of discarding 1733 kW. In fact, with 1677 kW as contract capacity, 53.25% of EVs were able to provide V2G to reduce their charging cost while increasing contract capacity to 1733 kW only 1% more increased in the V2G participation is observed.

As for the fleet size of 500, the optimum contract capacities lie in the interval 2055kW-2133kW as shown in Fig. 4. 6. To be noted, 2133kW is the smallest contract capacity size because its EV cost index close to 0. Table 4. 9 tells us that for 2600 kW as contract capacity the V2G participation reaches 61.2 % compared to 55.2 % for the upper bound of the chosen optimum range. The larger the contract capacity, the higher the V2G participation is.

The proposed approach outperforms the existing method for two reasons. First, the proposed approach considers aggregator satisfaction. Second, the proposed approach gives a range of optimum contract capacities. In contrast, the benchmark approach only considers the EVs distribution function and leaves the aggregator with only one choice.

Table 4. 7 Summary of one monte Carlos simulation on contract capacity optimization for fleet size 200

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Items | Values | | | | | | | | | |
| Contract capacity(kW) | 500 | 555 | 611 | 666 | 722 | 777 | 833 | 888 | 944 | 1000 |
| Charging cost ($) | 123.5 | 118.6 | 114.1 | 110 | 105.5 | 102 | 100.3 | 97.6 | 95.1 | 92.8 |
| Ratio of V2G vehicles (%) | 34 | 37.5 | 41 | 44.5 | 48 | 50.5 | 52 | 54.5 | 57.5 | 60.5 |

Table 4. 8 Summary of one monte Carlos simulation on contract capacity optimization for fleet size 400

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Items | Values | | | | | | | | | |
| Contract capacity(kW) | 1400 | 1455 | 1511 | 1566 | 1622 | 1677 | 1733 | 1788 | 1844 | 1900 |
| Charging cost ($) | 196.5 | 191.4 | 187.1 | 183.9 | 179.6 | 177.2 | 175.6 | 172 | 168.1 | 164.2 |
| Ratio of V2G vehicles (%) | 45.5 | 47 | 48.75 | 50.25 | 52 | 53.25 | 54.25 | 56.25 | 58 | 60 |

Table 4. 9 Summary of one monte Carlos simulation on contract capacity optimization for fleet size 500

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Items | Values | | | | | | | | | |
| Contract capacity(kW) | 1900 | 1977 | 2055 | 2133 | 2211 | 2288 | 2366 | 2444 | 2522 | 2600 |
| Charging cost ($) | 251.9 | 246.9 | 244.2 | 241 | 234.7 | 230.1 | 227.8 | 225.5 | 225.5 | 225.5 |
| Ratio of V2G vehicles (%) | 50 | 51.8 | 53.6 | 55.2 | 57.4 | 58.8 | 60 | 61.2 | 61.2 | 61.2 |

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| --- |
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Fig. 4. 4. Optimal contract capacities for EVs fleet size of 200.

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Fig. 4. 5. Optimal contract capacities for EVs fleet size of 400.

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Fig. 4. 6. Optimal contract capacities for EVs fleet size of 500.

1. Impact of PV Confidence Level and the Grid Request on the Charging Station Scheduling

Considering user satisfaction, the aggregator can set different confidence levels according to their risk appetite based on the uncertainty of PV output, as a result, a corresponding charging plan can be formulated.

Regarding Fig. 4. 7(a), charging plans at different confidence levels can influence enormously the charging cost of the EVs. For a grid request of 500kW, the charging cost increases as the PV confidence level increases.

The reason behind this is the availability of enough PV output power to fulfill the grid request, therefore there is no need to prompt all EV to discharge. However, for a high request from the grid that’s 1000kW the charging cost is largely reduced as the entire EV fleet can discharge. Fig. 4. 7(a) is about 200 EVs, while Fig. 4. 7(b) shows the information on the fleet size of 500.

The overall charging cost for a fleet size of 500 is greater than the fleet size of 200’ charging costs. The lowest charging cost is reached when the grid request is 2000 kW while for 200 EVs, 1000kW power request from the grid was enough to reach the minimal charging cost. The more vehicles the higher the grid power request must be to achieve the optimal charging cost.

|  |
| --- |
| (a) |
| (b) |

Fig. 4. 7. Impact of PV confidence level for EVs fleet size: 200 (a), (b)500.

1. Grid-CS Energy Exchange Economic Analysis

Since the chance constraint in the model is satisfied at a certain probability, there must be a case that the chance constraint is not satisfied, which could cause the underestimation of the PV power output leading to unsatisfied grid demand. This situation increases the EV user satisfaction, which is good for promoting EV adoption worldwide. Therefore, this paper quantifies the risk when the grid demand is not met and calculates the corresponding capacity of V2G to be injected to reduce any penalty due to an unsatisfied grid request.

Fig. 4. 8 depicts the situation where the confidence level in predicting the PV power is 0.2 while the grid request is 1000kW for the fleet size of 400. ESS and PV alone can’t meet the grid demand, a reliable agent is needed: the EVs fleet with V2G capabilities. By relieving the aggregator from the burden of not satisfying the grid demand EVs at the same time reduce considerably their charging cost from 266.85$ to 200.52$ equivalent to a 24.86% reduction in the total charging cost. The reference cost is the one achieved by considering the optimized G2V. The EVs fleet, ESS, and PV can work together to supply the energy needed upon the grid requests energy.

If we increase the fleet size from 400 to 500 by keeping the same grid demand as in Fig. 4. 9, the V2G dispatched power is reduced. The amount of power injected conjointly by ESS and PV is kept constant, the V2G capacity is the supplementary capacity. Not the whole capacity of V2G is needed but a fraction to fill the gap once PV and ESS can’t satisfy the grid demand. ESS is fully charged in the morning as there are few vehicles in the charging station. As a result, ESS is always available to supply energy to the grid.

At the same time, the grid demand may also be completely lower than what the charging station system can provide. Therefore, under the premise of taking aggregator’s satisfaction into account, as already mentioned PV and ESS are first deployed to meet grid demand. As depicted in Fig. 4. 10, with the fleet size of 200, only charging occurs for EVs, no V2G. Even though EVs are not doing any V2G they still minimize their charging cost as they are charged as much as possible at the lowest TOU price. As a result, their charging cost compared with the uncoordinated charging strategy cost is greatly improved from 268.35$ to 134.17$ corresponding to a reduction of 50%.

The uncoordinated charging pattern displayed in Fig. 4. 11 stipules that all the EVs start charging right away when they reach the CS. The uncoordinated charging strategy does not depend on the TOU, EVs are charged as soon as possible to meet their desired SOC. Their charging terminated around 2 pm while the optimized charging strategy minimized the charging cost instead.

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Fig. 4. 8. Fleet size 400 scheduled system power using 1000kW as grid request and PV confidence level of 0.2.

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| --- | --- |
| |  | | --- | |  | |

Fig. 4. 9. Fleet size 500 scheduled system power using 1000kW as grid request and PV confidence level of 1.

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| --- |
|  |

Fig. 4. 10. Fleet size 200 scheduled system power using 100kW as grid request and PV confidence level of 1.

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| --- |
|  |

Fig. 4. 11. Fleet size 200 scheduled EVs charging power under an uncoordinated charging strategy.

1. Influence of EV Penetration on Aggregator’s Profit

Aggregator profit has 4 components: ESS, PV, charging EV, discharging EV. Carefully analyzing Fig. 4. 12 we found that the first three, ESS, PV, and charging EV are permanent and the profit made from ESS is fixed as ESS is already been charged in morning hours since they are few EVs in the station at that time. However, the charging EV profit is flexible depending on the adoption of EV as a substitute for fuel vehicles. The more EV the highest the charging EV is. As for the profit from the V2G, it’s strongly proportional to the agreement of the user to let the aggregator discharge the vehicle. The profit made from the V2G decreases as the penetration level decreases. The question that may arise is what penetration is enough for the aggregator to realize a consequent profit from the new technology, that’s V2G.

Fig. 4. 13 shows that 60% of V2G penetration is enough for the aggregator to realize a significant profit from the V2G program. Penetration levels below 60% generate insignificant profit, while penetration above 60% does not add much on the profit made with a 60% penetration level. The margin above 60% can be neglected.

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|  |

Fig. 4. 12. Aggregator’s types of profit.

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| --- |
|  |

Fig. 4. 13. Aggregator tolerable V2G penetration level.

1. Conclusion and Future Prospects
   1. Conclusion

This thesis proposes a strategy to coordinate the exchange of energy between the grid and large charging station equipped with an energy storage system and photovoltaic panels. A win-win vehicle-to-grid approach considering both electric vehicle users and aggregator is devised, and the power assignment problems are formulated to guide the operations of the system. For the scheduling of the charging station system, we propose a contract capacity optimization algorithm which is practical for real-application operation since it relies on the joint-satisfaction of electric vehicle users and aggregator.

Moreover, we also formulate the energy exchange with the grid planning problem to include the intermittent nature of photovoltaic panels. Our simulation results show that, compared with the existing method, the proposed contract capacity optimization algorithm yields a range of unanimous eligible contract capacity sizes.

The key findings of this work are summarized as follows:

* Through Monte Carlos simulation, we captured electric vehicle behaviors and defined a joint utility function to guide the aggregator in subscribing to the optimal contract capacity.
* We established a sequence of entities to be used when it comes to energy exchange with the grid. Since the cost of producing photovoltaic power is neglected it's wise to make it the first entity to sell energy to the grid. Then follow the energy storage and the aggregated vehicle-to-grid.
* Thanks to chance-constrained programming we proved how the aggregated vehicles could be a reliable source of energy. By involving the vehicles into the exchange of energy with the grid, the aggregator reduces the risk of not being able to satisfy the grid demand.
  1. Future Prospects

This article concludes electric vehicles to be reliable energy sources but does not investigate how the entire society views the vehicle-to-grid program. Additional studies considering the total cost of ownership are needed to elucidate the advantages of the vehicle-to-grid program for the user in the long run. The future work of this article may consider how to motivate electric vehicle owners to participate in the vehicle-to-grid system on the one hand.

On the other hand, as to the charging station aggregator, additional studies to optimize the use of renewable energy sources and energy storage system are warranted. We intend also to extend our study to propose a reasonable algorithm in determining the size of energy storage system to be installed as well as the rating power of the photovoltaic panels to be purchased.

References

[1] F. Rassaei, W.-S. Soh, and K.-C. Chua, "Demand response for residential electric vehicles with random usage patterns in smart grids," *IEEE Transactions on Sustainable Energy,* vol. 6, no. 4, pp. 1367-1376, 2015.

[2] R. Yu, W. Zhong, S. Xie, C. Yuen, S. Gjessing, and Y. Zhang, "Balancing power demand through EV mobility in vehicle-to-grid mobile energy networks," *IEEE Transactions on Industrial Informatics,* vol. 12, no. 1, pp. 79-90, 2015.

[3] A. Y. Lam, K.-C. Leung, and V. O. Li, "Capacity estimation for vehicle-to-grid frequency regulation services with smart charging mechanism," *IEEE Transactions on Smart Grid,* vol. 7, no. 1, pp. 156-166, 2015.

[4] M. Nehrir *et al.*, "A review of hybrid renewable/alternative energy systems for electric power generation: Configurations, control, and applications," *IEEE transactions on sustainable energy,* vol. 2, no. 4, pp. 392-403, 2011.

[5] K. Chaudhari, A. Ukil, K. N. Kumar, U. Manandhar, and S. K. Kollimalla, "Hybrid optimization for economic deployment of ESS in PV-integrated EV charging stations," *IEEE Transactions on Industrial Informatics,* vol. 14, no. 1, pp. 106-116, 2017.

[6] L. Yao, Z. Damiran, and W. H. Lim, "Optimal charging and discharging scheduling for electric vehicles in a parking station with photovoltaic system and energy storage system," *Energies,* vol. 10, no. 4, p. 550, 2017.

[7] J. Pascual, J. Barricarte, P. Sanchis, and L. Marroyo, "Energy management strategy for a renewable-based residential microgrid with generation and demand forecasting," *Applied Energy,* vol. 158, pp. 12-25, 2015.

[8] C. Jin, X. Sheng, and P. Ghosh, "Optimized electric vehicle charging with intermittent renewable energy sources," *IEEE Journal of Selected Topics in Signal Processing,* vol. 8, no. 6, pp. 1063-1072, 2014.

[9] R. Wang, P. Wang, and G. Xiao, "Two-stage mechanism for massive electric vehicle charging involving renewable energy," *IEEE Transactions on Vehicular Technology,* vol. 65, no. 6, pp. 4159-4171, 2016.

[10] W. Tushar, C. Yuen, S. Huang, D. B. Smith, and H. V. Poor, "Cost minimization of charging stations with photovoltaics: An approach with EV classification," *IEEE Transactions on Intelligent Transportation Systems,* vol. 17, no. 1, pp. 156-169, 2015.

[11] A. Mohamed, V. Salehi, T. Ma, and O. Mohammed, "Real-time energy management algorithm for plug-in hybrid electric vehicle charging parks involving sustainable energy," *IEEE Transactions on Sustainable Energy,* vol. 5, no. 2, pp. 577-586, 2013.

[12] H. K. Nunna, S. Battula, S. Doolla, and D. Srinivasan, "Energy management in smart distribution systems with vehicle-to-grid integrated microgrids," *IEEE Transactions on Smart Grid,* vol. 9, no. 5, pp. 4004-4016, 2016.

[13] R. Mehta, D. Srinivasan, and A. Trivedi, "Optimal charging scheduling of plug-in electric vehicles for maximizing penetration within a workplace car park," in *2016 IEEE Congress on Evolutionary Computation (CEC)*, 2016: IEEE, pp. 3646-3653.

[14] P.-f. Zhang, W.-h. Shao, H.-n. Qu, W.-s. Xu, and Z.-y. Xu, "Study on charging strategy of electric vehicle parking lot based on improved PSO," in *2016 Chinese Control and Decision Conference (CCDC)*, 2016: IEEE, pp. 4456-4460.

[15] S. Sarabi, A. Davigny, Y. Riffonneau, and B. Robyns, "V2G electric vehicle charging scheduling for railway station parking lots based on binary linear programming," in *2016 IEEE International Energy Conference (ENERGYCON)*, 2016: IEEE, pp. 1-6.

[16] C. Jin, J. Tang, and P. Ghosh, "Optimizing electric vehicle charging with energy storage in the electricity market," *IEEE Transactions on Smart Grid,* vol. 4, no. 1, pp. 311-320, 2013.

[17] M. Ş. Kuran, A. C. Viana, L. Iannone, D. Kofman, G. Mermoud, and J. P. Vasseur, "A smart parking lot management system for scheduling the recharging of electric vehicles," *IEEE Transactions on Smart Grid,* vol. 6, no. 6, pp. 2942-2953, 2015.

[18] C. Jin, J. Tang, and P. Ghosh, "Optimizing electric vehicle charging: A customer's perspective," *IEEE Transactions on Vehicular Technology,* vol. 62, no. 7, pp. 2919-2927, 2013.

[19] S. Gao, K. Chau, C. Liu, D. Wu, and C. C. Chan, "Integrated energy management of plug-in electric vehicles in power grid with renewables," *IEEE Transactions on Vehicular Technology,* vol. 63, no. 7, pp. 3019-3027, 2014.

[20] B. Wang, P. Dehghanian, and D. Zhao, "Chance-constrained energy management system for power grids with high proliferation of renewables and electric vehicles," *IEEE Transactions on Smart Grid,* 2019.

[21] H. Liu, Y. Zhang, S. Ge, C. Gu, and F. Li, "Day-ahead scheduling for an electric vehicle PV-based battery swapping station considering the dual uncertainties," *IEEE Access,* vol. 7, pp. 115625-115636, 2019.

[22] A. Aldik, A. T. Al-Awami, E. Sortomme, A. M. Muqbel, and M. Shahidehpour, "A planning model for electric vehicle aggregators providing ancillary services," *IEEE Access,* vol. 6, pp. 70685-70697, 2018.

[23] H. Turker, A. Radu, S. Bacha, D. Frey, J. Richer, and P. Lebrusq, "Optimal charge control of electric vehicles in parking stations for cost minimization in V2G concept," in *2014 International Conference on Renewable Energy Research and Application (ICRERA)*, 2014: IEEE, pp. 945-951.

[24] A. Hoke, A. Brissette, D. Maksimović, A. Pratt, and K. Smith, "Electric vehicle charge optimization including effects of lithium-ion battery degradation," in *2011 IEEE Vehicle Power and Propulsion Conference*, 2011: IEEE, pp. 1-8.

[25] A. Hoke, A. Brissette, K. Smith, A. Pratt, and D. Maksimovic, "Accounting for lithium-ion battery degradation in electric vehicle charging optimization," *IEEE Journal of Emerging and Selected Topics in Power Electronics,* vol. 2, no. 3, pp. 691-700, 2014.

[26] M. A. Ortega-Vazquez, "Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty," *IET Generation, Transmission & Distribution,* vol. 8, no. 6, pp. 1007-1016, 2014.

[27] H. Zhang, Z. Hu, Z. Xu, and Y. Song, "Evaluation of achievable vehicle-to-grid capacity using aggregate PEV model," *IEEE Transactions on Power Systems,* vol. 32, no. 1, pp. 784-794, 2016.

[28] Z. Yang, L. Sun, M. Ke, Z. Shi, and J. Chen, "Optimal charging strategy for plug-in electric taxi with time-varying profits," *IEEE Transactions on Smart Grid,* vol. 5, no. 6, pp. 2787-2797, 2014.

[29] "Energy Online." ISO New England. <http://www.energyonline.com/> (accessed.

[30] S. Guner, A. Ozdemir, and G. Serbes, "Impact of car arrival/departure patterns on EV parking lot energy storage capacity," in *2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2016: IEEE, pp. 1-5.

[31] X. Chen, K.-C. Leung, A. Y. Lam, and D. J. Hill, "Online scheduling for hierarchical vehicle-to-grid system: Design, formulation, and algorithm," *IEEE Transactions on Vehicular Technology,* vol. 68, no. 2, pp. 1302-1317, 2018.

[32] T. He, J. Zhu, J. Zhang, and L. Zheng, "An optimal charging/discharging strategy for smart electrical car parks," *Chinese Journal of Electrical Engineering,* vol. 4, no. 2, pp. 28-35, 2018.

[33] G. R. C. Mouli, M. Kefayati, R. Baldick, and P. Bauer, "Integrated PV charging of EV fleet based on energy prices, V2G, and offer of reserves," *IEEE Transactions on Smart Grid,* vol. 10, no. 2, pp. 1313-1325, 2017.

[34] A. S. Awad, M. F. Shaaban, T. H. El-Fouly, E. F. El-Saadany, and M. M. Salama, "Optimal resource allocation and charging prices for benefit maximization in smart PEV-parking lots," *IEEE Transactions on Sustainable Energy,* vol. 8, no. 3, pp. 906-915, 2016.

[35] L. Agarwal, W. Peng, and L. Goel, "Probabilistic estimation of aggregated power capacity of EVs for vehicle-to-grid application," in *2014 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2014: IEEE, pp. 1-6.