Tarun Verma and Lalit Kumar (October2023) OPTIMIZATION AND CONTROL STRATEGIES FOR INTEGRATING ELECTRIC VEHICLES IN POWER DISTRIBUTION NETWORKS
***International Journal of Economic Perspectives*, *17*(10) 71-80**
Retrieved fromhttps://ijeponline.com/index.php/journal

OPTIMIZATION AND CONTROL STRATEGIES FOR INTEGRATING ELECTRIC VEHICLES IN POWER DISTRIBUTION NETWORKS

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ABSTRACT

The key findings from the study subject are summarized in this publication. The study begins with an introduction to the power market, battery modeling, & vehicle driving patterns, as these are major inputs required in an optimal charging issue for an electric car. The main results are then presented, which include an in-depth examination of three control strategies created for electric vehicle integration as well as four developed methods, namely problem formulations of optimal imposing schedules for electric vehicles using linear simulation, interactive computer programming, mix integer linear development, & data modeling based processes.

Keywords: battery modeling, & vehicle driving pattern, control strategies and electric vehicle integration

INTRODUCTION

The DanishEdison project [1] provides an overview of the present Nordic power industry as well as how electric cars can be incorporated into existing and future markets [2,3]. Energy is transferred in the Nordic power market through direct trading between players (bilateral trade) & through Nordic power exchange, NordPool. Within NordPool, there are 2 primary markets for energy exchange: Elspot for day-ahead trade & Elbas for balancing.Elspot is a day-ahead market that trades hourly exchanges. Because both buyers and sellers placed bids, the method of computing price is known as double auctions. The day-ahead price is calculated by NordPool Spot's algorithm in Oslo at noon.

NordPool Spot announces the pricing once the computation is complete. Simultaneously, NordPool Spots informs participants how much power they have purchased or sold for each hour of following day. These purchasing and selling reports are also supplied to TSO in NordPool spot area. The TSO uses this information to compute the equilibrium energy for each participant later on. In addition to determining day-ahead pricing, Elspot market is used to control day-ahead congestion in Nordic area. Market splitting is a day-ahead congestion management strategy. More information on market segmentation may be found in [4,5].

The transmission system operator [6] manages the regulatory power market in order to get ancillary services in transmission grid. It is possible that consumption will surpass (or lag behind) generation. In this instance, alternating current frequency will fall to (exceed) a value less than (greater than) 50 Hz. As renewable energy becomes a more essential resource for decreasing emissions from fossil fuels, production will become more unreliable, & therefore the demand for power regulation is expected to grow. [2,7].

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BATTERY MODELING

In general, there are 2 approaches to modeling charging characteristics of electric cars, namely battery. The individual battery pack approach is one option, while the aggregated or cell-based form is another. When exploring optimal charging or discharging problem, most of the research evaluated treated it as a battery pack for simplicity. Most battery model research now focus on three distinct aspects. [8, 9]:

- The first & most widely used model is known as a performance or charge model, & it focuses on modeling battery's state of charge, that's single most critical parameter in system evaluations.
- The voltage model is used to represent terminal voltage so that it may be utilized in more extensive modeling of battery management system and more detailed assessment of battery losses.
- The third sort of model is lifetime model, which is used to estimate influence of a certain operating strategy on battery's projected lifespan.

Because the current study is primarily concerned with smart charging of electric vehicles, we will focus on the first feature, namely simulating state of charge of the batteries during operation.

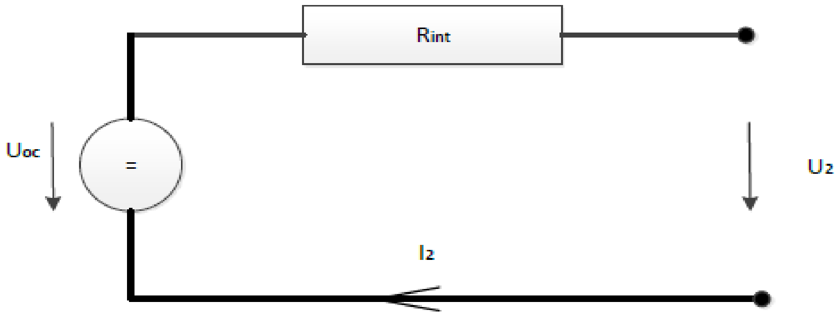

Figure 1: Equivalent circuit of a battery

Consider a comparable system circuit, such as the one shown in Fig. 1, to create a simplified physical model of a battery. The steady state battery analog circuit has mostly been applied to lead acid batteries, although it has also been applied to nickel cadmium, nickel metallic hydride, and lithium-ion cells. In this circuit, battery is symbolized by a voltage source coupled in serieswith an internal resistance. Kirchhoff's law provides following set of formulas for equivalent circuits:

$$U_{oc}(t) - R_{int}(t).I_2(t) = U_2(t)\text{..................}(1)$$

Both voltage source $U_{oc}(t)$ & internal resistance $R_{int}(t)$ are dependent on state of charge (soc) of battery.

The terms kWh and Ah are frequently used to describe capacity of a battery. If fluctuations of battery's state of charge are calculated by adding kWh to available capacity, the procedure typically startswith calculating inside capacity of battery, which can be calculated linearlyor exponentially with external enforcing power, as demonstrated in the study [10]. The difference among 2 imposing schedules using linear roughly & not linear approximate (second-order Taylor series expansion) is minor, suggesting that use of linear approximation is adequate & benefit of using a nonlinear rebuilding does not justify increase in computational time, according to studies [10]. If, as in the study [11,12], the dynamic of the battery's level of charge is defined by calculation of dynamics of electric charge, dynamic software is generally used to design ideal charging of an electric car.

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DRIVINGPATTERN AND ASSOCIATEDELECTRICITY CONSUMPTION

The analysis of driving pattern can be divided into 2 main directions:

- Utilization of electric cars, or when & how long electric vehicle will be utilized in following scheduling period, which in current research is 24 hours. This is due to the fact that when and how long determine the amount of energy that must be obtained or charged for following scheduling period.
- Because placement of electric vehicles inside network determines where the grid may become crowded, the location of the electric vehicles while charging & how numerous of them will be charged at the same time.

Most studies [10,11] assume that fleet operator understands driving habits of the consumers and can thus estimate the power usage. There have been few research on the driving pattern. In the Danish situation, Kristoffersen et al. [13] examined a strategy for constructing driving patterns from historical data. Clustering survey responses on vehicle fleet in West Denmark produces realistic driving patterns for every car user. S. Shahidinejad et al. [14] developed a daily duty cycle that provides a comprehensive data set for optimizing users' energy needs. Furthermore, this data is used to estimate the impact on the electric utility grid of a fleet of plug-in electric vehicles recharging during day, which may result in a peak consumption during day that must be met by local utility grid. Intra-city or short-term in the travel routines are generally fairly predictable due to predetermined hours of work and regular corporate schedules and itineraries.

This study's driving pattern is based on 2003AKTA Survey [15], in which 360 autos in Copenhagen were tracked using GPS for 14 to 100 days. The start and end times, as well as the length and distance, are all included in each data file. The original data is transformed into 15-minute interval driving energy demands based on assumption that an electric car requires 15 kWh per 100km (the number often varies between 11 kWh and 18 kWh per 100 km). Based on the investigation's findings, some simulated driving data for electric vehicles was generated from the database [16].

[16] offers a Danish driving pattern investigation, which reveals that average daily driving distance in Denmark is 42.7 km. Using a 0.15 kWh/km figure for electric automobile energy use per kilometer, the monthly energy need for a battery-powered vehicle will be around 192 kWh (42.7 km*30*0.15kWh/km). Using the Nissan Leaf as an example (EV battery capacity is 24 kWh), buyers would have to power Leaf about eight times (192 kWh/24 kWh). Owners, on the opposite hand, seldom empty their Leaf completely before charging it. For discussion purposes, it is assumed that users would charge electric car twenty times each month, yielding 9.6 kWh of energy each time. They would recommend a five-hour charging period (9.6 kWh/2.3 kW) under the current circumstances. The driving data is chosen at random & converted into a 15-minute intervals driving energy need with an average of 9.6 kWh.

MAIN RESULTS

1. CONTROLSTRATEGIES FOR INTEGRATINGELECTRIC VEHICLES

Several economic opportunities have been recognized as a result of the EV fleet, such as offering auxiliary services to transmission system operations & storing services to renewable energy providers. A fleet operator has been proposed to manage EVs in order to capitalize on commercial potential. Fleet operators [17, 18] might be independent or incorporated into an energy supplier's current business function. Furthermore, the fleet operator must collaborate with distribution system operator to control distribution network congestion. In general, FOs can employ one of two control structures to realize economic opportunities: centralized control or

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decentralized control. The grid restriction from distribution grid should be addressed in both control schemes.

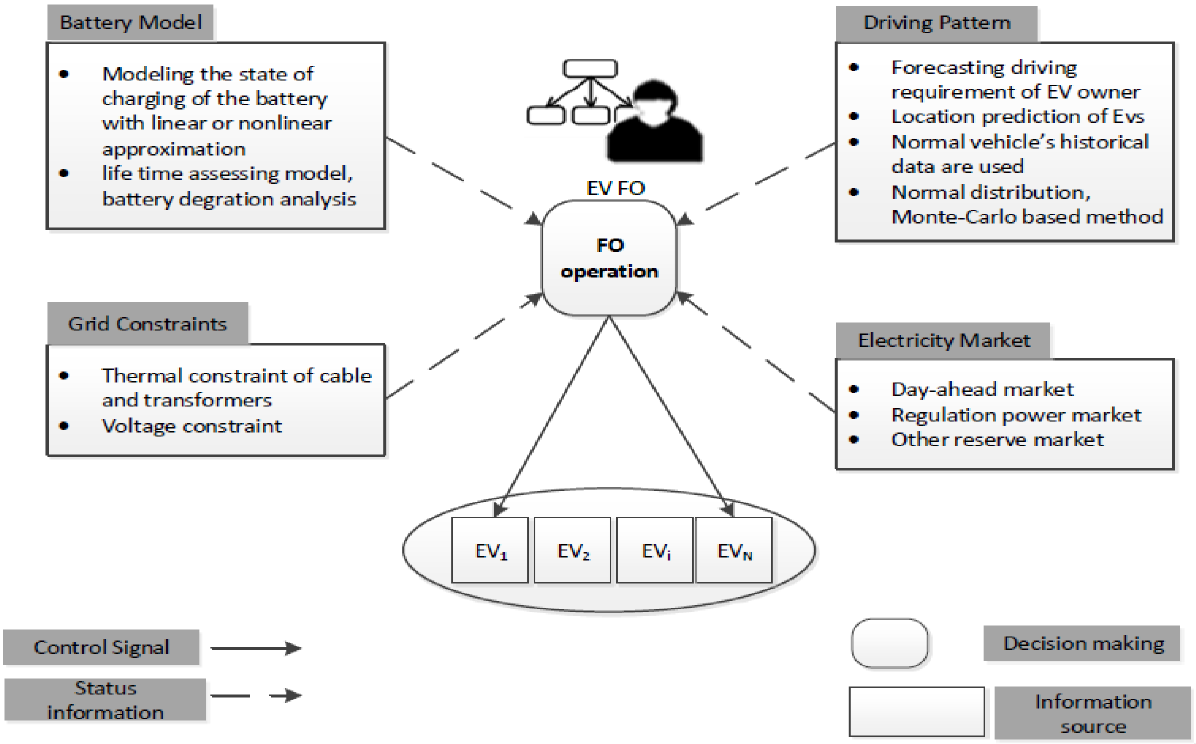

Figure 2: Centralized control: primary inputs & output of electric vehicle fleet operator

In centralized control, electric cars are aggregated & directly managed by the fleet operator, for example, by prescribing charging schedules. In a decentralized architecture, control is implemented as a price signal, i.e. individual EV optimizes charging schedule depending on power price information provided by FO or utility.Figure 2 displays four key inputs for developing control techniques for centralized control. TheFO gathers all necessary information, such as the battery model, driving habits, grid limits, & power pricing, & creates a charging schedule for each EV centrally. In setting of decentralized charging, on the other hand, the FO employs pricing signals to coordinate charging behavior of EV customers. Two approaches to providing decentralized charge control are discussed. Figure 3 depicts information flow architecture in decentralized charging control. The basic idea underlying the market-based control system represented in Fig. 3(a) is that EVs alter their electrical charging profiles independently in response to price signal; FO leads these changes by changing price signal. Implementation often necessitates numerous iterations. The price management technique depicted in Fig. 3 (b) necessitates FO forecasting customer. reactions to pricing. Simple time-of-use pricing or escalating prices might be used as the price indication.

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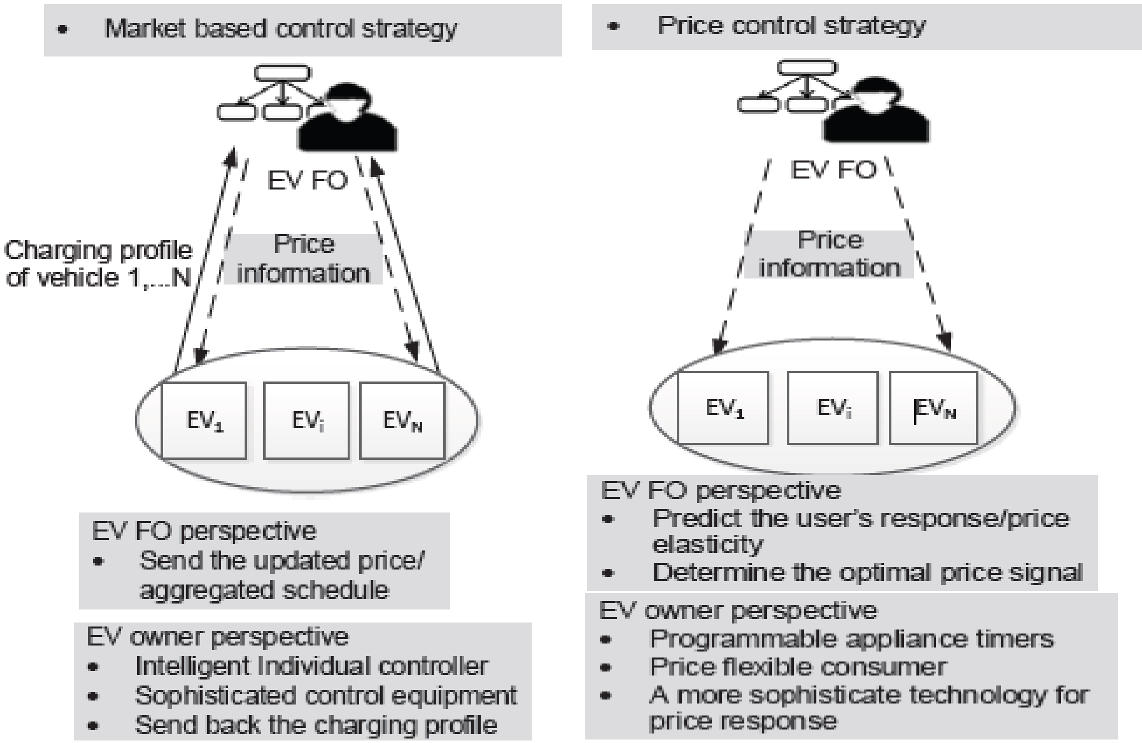

(a) **(b)**

Figure 3: Decentralizedcontrol: a schematic view ofinformation flow below eet operator & electric vehicles

2. FORMULATIONOF THE OPTIMALCHARGING OFELECTRIC VEHICLES BY CENTRALIZEDCONTROL ARCHITECTURE

In this section, we will discuss how to create ideal charging plan for electric cars using linear programming, dynamicalprogramming, & mixed integerprogramming approaches.

Linearprogramming based optimalcharging schedule generation

As previously stated, the linear approximation approach is used in this work. A linear programming technique is used to optimize an EV fleet's charging schedule, taking into consideration both spot pricing & individual EV driving requirements, with objective of minimizingcharging costs. A simplified version ofFig. 2 is utilized to assist construction of the control algorithm. The EV fleet's charging plans areoptimized separately, & then each EV's schedule is aggregated, because it is assumed that each individual's driving requirements shouldbe satisfied & computed independently. The following is an example of the formulation:

$$minimize \sum_{i=1}^{N_T} \Phi_{j,i} \,.\, P_{j,i} \,.\, t, j = 1, \dots, N_k^E$$

subject to

$$\begin{cases} SOC_{0,j} + \sum_{i=1}^{n_T} P_{j,i} \cdot t_{j,i} \geq SOC_{Min,j} + \sum_{i=0}^{n_T - 1} E_{d,i+1} \\ SOC_{0,j} + \sum_{i=1}^{n_T} P_{j,i} \cdot t_{j,i} \leq w \cdot E_{cap,j} + \sum_{i=2}^{n_T+1} E_{d,i-1} \\ 0 \leq P_{j,i} \cdot t_{j,i} \leq P_{max,j} \cdot t_{j,i},\ i = 1, \dots, N_T \end{cases} \quad (2)$$

With above optimization problem, FO can generate a unique energy schedule for EV owner; sum of individual EV energy schedule will be denoted as $P_{k,i}^E$, &

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$P^E_{k,i} = \sum_{j=1}^{N^E_k} P_{j,i,}, \quad k = 1, \dots N_B, i = 1, \dots, N_T,$

where

N^E_k = Number of EVs under FO k.
N_T = Number of time slot in scheduling period.
N_B = Number of FOs.
j = Index for number of EVs under each FO, j = 1, 2,..., N^E_k
i = Index of time slot in scheduling period, i = 1, 2,..., n_T,..., N_T
k = Index for number of FOs, k = 1, ..., N_B.
$\Phi_{j,i}$ = Predicted day-ahead electricity market price vector.
$P_{j,i}$ = Decision variable vector.
t = Length of each time slot.
$P^E_{k,i}$,= Power requirements of EVs of each FO in each time slot.
$SOC_{o,j}$ = Initial state of charge of individual EV.
$SOC_{Min,j}$ = Recommended minimum state of charge of EV.
E_d = The predicted individual EV owner's driving requirement.
$P_{max,j}$ = Charge rate in term of energy of individual EV.
w * $E_{cap,j}$ = Recommended maximum state of charge of EV,
where w is parameter which express charging behavior of battery of EV is a linear process, $E_{cap;j}$ is capacity of battery of EV.

The first constraint in Eq. (2) stipulates that the battery's available energy must be more than or equal to power required for next voyage. The second restriction is that energy supply in storage device must be less than or equal to power capacity of battery. The third restriction is that speed of charging must be below or equal to the maximum electrical rate of the charger. The practical meaning of decision factor vector Pj;i is to decide whether to distribute/charge electricity within specific time slots when charging cost may be minimized.

Dynamicprogramming based optimal charging schedule generation

As previously said, evaluates dynamics of battery's state of charge utilizing electric charge. The study's management architecture is similarly a reduced version of the one presented in Fig 2. The time horizon [0; N] of a day is divided into equidistant intervals of time [k; k+1] for day-ahead scheduling, with k = 0,..., N-1. The time interval is assumed to be t. This issue is handled by studying separate system that describes battery:

$$x_{k+1} = T(x_k, u_k, k)\text{........................}(3)$$

Statevariable x_k represents state of charge of battery at time k. x_k is notonly discrete in time(index k) but also in value. Any value has to be included in predefined set X, which can be calculated by a function of charge Q_k & total capacity Q_{max}.

$$x_k = \frac{Q_k}{Q_{max}}\text{......................................}(4)$$

u_k in equation 3 is control variable, which is dimensionless & discrete. u_k is multiplied with maximum available charge power (P_{max}) when electric vehicle is connected with grid. The values of u_k are fixed at 0when driving, while these values range from0 to 1 when electric vehicle isconnected to grid. If U_{plug} is set thatcovers all possible values of uk, its discretization may be described as follows:

$$u_k = \begin{cases} u_k \in U_{plug}, & k \in K_{plug} \\ u_k = 0, & k \in K_{driv} \end{cases} \qquad (5)$$

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K_{plug} is a set of indices k within time periods where vehicle isplugged in,while K_{driv} refers to driving intervals. The summation of number ofelements in K_{plug} & K_{driv} is N, total number oftime intervals. Any index k in K_{plug} or K_{driv} has to beelement of predefined set K.

$$k \in K = \{K_{plug}, K_{driv}\} \qquad (6)$$

Aspecific controlstrategy is represented by

$$u = \{u_o, u_1, u_2,..., u_{N-1}\} \qquad (7)$$

Any value of u_k has to be element of a predefined set U, which is known as set of admissible decision. The total cost of a sequence, $\int_0^U$, is given by cost of final step, $f_N(x_N)$, plus cost for all other previous steps, $v_k(x_k, u_k, k)$, then we have:

$$\int_0^U (x_0) = f_N(x_N) + \sum_{k=1}^{N-1} v_k(x_k, u_k, k) \qquad (8)$$

The optimal control strategy $u^* = \{u_o^*, u_1^*, u_2^*, ..., u_{N-1}^*\}$ minimizes cost function 8 & can be determined by dynamic programming.

Mixed integerlinear programming basedoptimal charging & dischargingschedule making

Analyze the annual expenditures of four different charging schemes, including night charging, night charging with V2G, and 24 hour charging, in order to investigate economics of vehicle to grid technologies, such as supplying auxiliary service to the regulatory power market. The research is divided into two stages. The numerical comparison of four charging techniques in the first phase only covers charging cost (chargingcost equals cost of received power minus profits from applying V2G). This is performed by solving a mixed integer computing problem with purpose of reducing charging costs while taking into account driving needs of consumers & practical constraints of EV battery (battery capacity, optimal state of charge range). A problem statement is as follows:

$$min \sum_{i=1}^{N} \left\{ \Delta E_c(i) \cdot \Phi(i) \cdot \frac{u_1(i)}{\eta_c} + \Delta E_d(i) \cdot \Phi(i) \cdot u_2(i) \cdot \eta_d \right\}$$

Subject to

$$\begin{cases} E(i) = E_0 + \sum_{k=1}^{k=i} \{\Delta E_c(k) \cdot u_1(k) + \Delta E_d(k) \cdot u_2(k) - E_d(k) \cdot u_3(k)\} \\ \delta_{min} \cdot E_{cap} \leq E(i) \leq \delta_{max} \cdot E_{cap} \\ E_d(i+1) \cdot u_3(i+1) \geq E(i) \\ 0 \leq \Delta E_c(i) \leq P_{c,max} \cdot \eta_c \cdot \Delta t \\ -\frac{P_{d,max}}{\eta_d} \leq \Delta E_d(i) \leq 0 \\ u_1(i) + u_2(i) + u_3(i) = 1 \end{cases} \qquad (9)$$

where $\Phi_{(i)}$ is electricity price & $E_d(i)$ denotesdriving energy requirements. The decision variables $\Delta E_c(i)$ & $\Delta E_d(i)$ represent energy charged into & discharged from battery in each time interval respectively, while other three binary variables $u_1(i)$; $u_2(i)$; $u_3(i)$ indicate on/off status of charging, vehicle to grid (discharging), & driving foreach corresponding time interval.

To facilitate formulation, an intermediate variable E(i) is introduced representing energy level of battery at end of each time interval. Parameters E_{cap} & E_o represent nominal energy capacity and initial energy of battery in planning period, while charging & discharging efficiency are represented by η_c & η_d. The maximum power exchanged b/w EV inverter & electrical grid are expressed by $P_{c;max}$ charging & $P_{d;max}$ discharging respectively, which constrains maximum energy

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exchanged b/w electric vehicle & grid. Concerning battery life, δ_{min} & δ_{max} are further introduced to represent manufacturer recommended sate of charge (SOC) range.

The rain flow counting technique is employed in second phase, or post processing stage, to measure lifetime consumption of a lithium-ion EV battery for four charging strategies. The battery lifetime consumption for different charging strategies is computed by applying rain flow counting method to monthly charging profiles established in first phase & taking relationship b/w number of cycles & depth of discharge into account. Finally, a simple method for estimating the yearly cost of various billing strategies is presented:

$$C_{ann} = (C_{capacity} + C_{charging})/L_{exp} \qquad (10)$$

where $C_{capacity}$ & $C_{charging}$ represent capital cost of battery & charging cost incurred during battery lifetime respectively, & L_{exp} indicates expected lifetime for different charging schemes. This is a comprehensive annual cost estimation. The analysis found that the night charging plan is the least expensive of the four charging schemes tested. For parameters values & calculation results, for example,

3. FORMULATIONOF THE OPTIMALCHARGING OFELECTRIC VEHICLES USING DECENTRALIZED CONTROLARCHITECTURE

Pricecontrol is being investigated for decentralized control architecture. The price management strategy, as shown in Fig. 3 (b), needs FO to forecast the consumers' reactions to the pricing. A statistical model of demand elasticity introduced in [19] is utilized in this work to investigate how pricing can govern the charging behavior of EV users. The marginal utility function of loads is achieved in model by following parametric random process:

$$r(t) = \begin{cases} \beta - \delta(t-\alpha), & \alpha \le t \le \alpha + \gamma \\ 0, & otherwise \end{cases} \qquad (11)$$

where $\alpha, \beta, \gamma, \delta$ are random variables that describes different characteristics of utility function as follows:

- α stands for time slot that a task is initially requested, which also reflects task distribution.
- β is initial marginal utility, which stands for magnitude of marginal utility.
- γ is tolerable delay, which determines maximum delay that a user can tolerate to finish a task.
- δ means utility decay rate, which represents cost of inconvenience by delay.

The scheduling of each individual job is now a random event whose distribution of probabilities is governed by stochastic process r(t) in this framework. Expectation with regard to distribution of r(t) can be utilized for estimating the aggregating demand curve. It should be noted that certain presumptions have been made previously, such as the arranging period being divided into T time slots, M individual jobs total m: m = 1;...;M of various electric cars that must be initiated by all users inside scheduling time, with each job using xm kWh energy, totaling X0 as the overall amount of energy utilized to be planned within target organizing period. Furthermore, it is assumed that each work may be completed in a single time slot; hence, activities lasting more than one time slot will be broken into many tasks that are assessed independently.

CONCLUSIONS

This study focuses on commercial players, such as fleet operators, and their control tactics. However, the utility can employ some strategies to coordinate charging profiles of electric cars. Centralized control and pricing control were among control systems examined. Three algorithms were employed to create approaches for centralized control. It is suggested that a

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linearprogramming-based method be used to characterize optimal charging scheduling difficulties. The suggestion is based on its overall performance & speed of computing. In terms of pricing control, it has been proved that a price signal is an efficient means of regulating charging behavior of electric cars; nevertheless, further study is required in order to create a good rate that may alleviate the uncertainty generated by utilizing price control.

Given the realistic operations of fleet operators, it is anticipated that EVs must subscribe to one FO, maybe by signing a contract that is valid for a set amount of time. Such a subscription might potentially follow existing geographical regions, i.e., neighborhood served by a single FO from a single substation. In this context, the mobility of electric vehicles will also necessitate roaming-related agreements/standards among different FOs, as well as a standardized messaging & data infrastructure, to ensure that fleet operators have immediate access to EV news when electric vehicles switch between operators.

Forecasted power prices and expected EV driving patterns are required to develop an ideal charging plan; thankfully, they are predictable. The correct approach to pick among the provided control schemes relies on the situation (assume the electric vehicles can be either direct controlled or price coordinating). Here are a few company scenarios to consider:

- In scenario 1, FOs only participate in day ahead market to save energy expenses; direct control alongside with linear programming-based technology is advised.
- In scenario two, FO would want to participate in both day-ahead spot market & regulatorypower market; but, because to high chance ofwaiting resource arrangements & activation, direct oversight remains ourpreferred option.
- In scenario three, FO will work with DSO to reduce peak load; either directcontrol or price regulation can be utilized; each option has advantages & disadvantages; for example,price control is easier to implement than direct surveillance, although direct control assures a low risk.

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